**IN THE UNITED STATES DISTRICT COURT**
**FOR THE DISTRICT OF MARYLAND**

| | | |
|---|---|---|
| WIKIMEDIA FOUNDATION, | ) | |
| Plaintiff, | ) | |
| | ) | Civil Action No. 1:15-cv-00662-TSE |
| v. | ) | |
| NATIONAL SECURITY AGENCY, *et al.*, | ) | |
| Defendants. | ) | |

Exhibit 7

**IN THE UNITED STATES DISTRICT COURT**
**FOR THE DISTRICT OF MARYLAND**

| | | |
|---|---|---|
| WIKIMEDIA FOUNDATION, | ) | |
| Plaintiff, | ) | |
| v. | ) | No. 1:15-cv-0662 (TSE) |
| NATIONAL SECURITY AGENCY, *et al.*, | ) | |
| Defendants. | ) | |

# DECLARATION OF DR. ALAN J. SALZBERG

Dr. Alan Salzberg, for his declaration pursuant to 28 U.S.C. § 1746, deposes and says as follows:

## I. Introduction

1. I am the Principal (and owner) of Salt Hill Statistical Consulting. My work includes statistical sampling, analysis, and review for government and industry. I was asked by the U.S. Department of Justice to review the Declaration of Jonathon Penney filed on December 18, 2018 in the above-captioned case. ("Penney Declaration"). In particular, I was asked to assess and provide my conclusions concerning the validity of both the statistical conclusions reached in the Penney Declaration and the underlying methodology.

2. The Penney Declaration presents an empirical data analysis of Wikipedia page-view data and concludes that "public awareness of NSA surveillance programs, including Upstream surveillance, which became widespread during the June 2013 Snowden disclosures, is highly likely to have had a large-scale chilling effect on Wikipedia users."[1] My review analyzes the data, methodology, and conclusions presented in the Penney Declaration.[2]

3. This declaration proceeds as follows. In the next section, I summarize my opinions. In Section III, I review my qualifications. In Section IV, I detail the reasons for my opinions. And in Section V I set forth my conclusions. Appendix I contains my programming code from which I produced the analyses contained in this report. Appendix II lists the documents and data I considered as part of this report. Appendix III contains my resume, publications for the last 10 years, and testimony history for the last four years. Appendix IV contains a graph showing page views by article for each of the 48 articles the Penney Declaration theorizes were influenced by a chilling effect. Appendix V contains the same 48 articles but for an extended time period that continues through November 2018. Appendix VI contains a graph showing page views by article for each of the 89 articles described in the Penney Declaration as comparative articles (which purportedly were not affected by the June 2013 disclosures). Appendix VII contains the aggregate graphs for each of the five comparison datasets.

## II. Summary of Opinions

4. In summary, I find that:

   A. The methodology used in the Penney Declaration—which purportedly shows an upward trend in page views of certain articles posted on Wikipedia through May 2013, followed by an abrupt drop and downward trend in views of those articles beginning in June 2013—is deeply flawed, inappropriate, and likely biased.

[1] Penney Declaration, paragraph 10.

[2] The Penney Declaration, in paragraphs 12 through 21, describes research on chilling effects theory. The Penny Declaration's stated conclusions in Paragraph 11 do not rely on that overview section, and I was not provided, nor does the Penney Declaration present, any data on this research. Therefore, I did not review or consider those paragraphs further. Furthermore, it does not appear that any of that research was specific to Upstream.

B. The Penney Model simply assumes that a single change occurred in June 2013, rather than letting the data identify the timing and number of changes in trends that occurred. Even though there is no consistent trend in the data, the design of the Penney Model will create the appearance that the data contain just one inflection point. And, because of its design—even though changes in trend occurred *before* these June 2013 disclosures—the Penney Model will find that the disclosures caused them.

C. Contrary to the hypothesis presented in the Penney Declaration, analysis of page views for the 48 individual articles in the privacy-sensitive group do not show a rising trend followed by an immediate and sustained drop in June 2013.

D. With the one exception of removing the article on Hamas, the Penney Declaration does no analysis or adjustment for factors (such as world events) affecting these individual article page views. Instead, the Penney Declaration inappropriately aggregates the vastly different page view data for individual articles, with the result that these individual differences in page views are masked.

E. Even at that aggregate level, I find that the hypothesized peak in page views of "privacy-sensitive" articles in May 2013 does not exist, and the hypothesized upward and then downward trends in views of privacy-sensitive articles before and after June 2013, respectively, do not exist.

F. Extended data through 2018 regarding page views of the privacy-sensitive articles do not indicate a long-term decline in page views from pre-June 2013 levels.

G. A proper control dataset would exhibit similar page view behavior prior to June 2013. The comparison datasets used in the Penney Declaration do not and are thus inappropriate controls.

H. The Penney Declaration analysis ends in July 2014. No data are presented that shed any light on whether page views at the time the Amended Complaint was filed in 2015 (or thereafter) were affected by Upstream. In other words, even if the purported effect and trends were a correct conclusion for the data examined (and they are not), the Penney Declaration analysis does not and cannot show that the effect continued years after the study ended.

I. Even if a chilling effect occurred in June 2013, there are no data analyzed in the Penney Declaration that show any effect was due specifically to "public awareness of" the specific NSA surveillance program challenged here (known as Upstream surveillance) rather than possible inaccuracies, if any, about the program reported in the press, disclosures about other NSA programs, disclosures about other surveillance programs (e.g., surveillance by Britain), or other, unrelated events of June 2013.

I describe the analyses that led to these findings in Section IV.

## III. Qualifications

5. I am the Principal of Salt Hill Statistical Consulting. My work includes statistical sampling, analysis, and review for government and industry. Many of my consulting projects and research papers relate to the detection and measurement of bias. On several occasions, I have written expert statistical reports or testified as a statistical expert, both in court and in depositions. My current and recent work includes:

    - Statistical analysis and modeling regarding the valuation of residential mortgages. Assisted in developing complex models to evaluate portfolios of loans affected in the housing crash of 2008.

    - On behalf of several state public service commissions, directed data analysis and statistical design in a series of systems tests of Bell South, Verizon, SBC-Ameritech, and Qwest. Testified before several state public service commissions, including New York, Virginia, Florida, Michigan, and Colorado. Co-inventor of U.S. Patent related to this work.

    - For a major pharmaceutical company, analyzed company and external marketing data to determine reliability and potential biases in using external data sources. Analyzed physician-specific data for a period of 36 months concerning product marketing to approximately 1 million prescription drug subscribers.

    - Statistical sampling and analysis, including regression modeling and survival analysis, on behalf of the U.S. Department of Labor.

    - Statistical review of the sampling and estimation methodology used to audit Medicaid providers in New York State. Work was performed on behalf of the New York State Office of Medicaid Inspector General.

6. I received a Ph.D. in Statistics from the University of Pennsylvania, where I also received a B.S. in Economics. I have taught courses in statistics and quantitative methods at the University of Pennsylvania and American University and have published statistics papers in peer-reviewed journals. I am also the co-inventor on a U.S. Patent (#6,636,585) for a statistical process design to test the systems of telecommunications companies. A copy of my résumé is attached as Appendix I to this Report, which also includes all publications within the last ten years and a list of testimony within the last four years. My company is being compensated at a rate of $560 per hour for my work in this matter.

## IV. Details of Findings

### A. Background and Data

7. The analysis presented in the Penney Declaration uses eight datasets to analyze a hypothesized “chilling effect” on Wikipedia users due to “public awareness of NSA

surveillance programs, including Upstream surveillance."[3] The first three datasets (which I will call the "Terror" datasets) contain monthly page-view information for 48 so-called "privacy-sensitive" Wikipedia articles that Dr. Penney selected because they contain terms included in a 2011 U.S. Department of Homeland Security list of "terrorism related keywords."[4] These three overlapping datasets contain page views for Wikipedia articles from January 2012 through August 2014 ("study period").[5] The first dataset contains the monthly page views, by article, for each of the 48 articles, by month, for the study period. I will call this dataset "Terror 48."[6] The second dataset contains monthly page views for 47 articles, which are comprised of all of the original 48 articles except for the article on "Hamas." I will call this dataset "Terror 48 without Hamas." The third dataset, which I will call "High Privacy 31," contains page-view data for 31 of the 48 articles deemed most "privacy-concerning" by the Penney Declaration.[7]

8. The Penney Declaration also considers five comparison datasets. According to the Penney Declaration, these datasets include two datasets of total global article views (which I call "Global 1" and "Global 2");[8] 25 domestic-security related articles ("Security 25"); 34 infrastructure articles ("Infrastructure 34"); and 26 popular ("Popular 26") articles.[9]

9. I supplemented the data in the Penney Declaration using publicly available data from Wikimedia to capture information on page views for each of the Terror 48 articles for the time period from July 2015 through November 2018. Therefore, for some of my analyses, I use data from January 2012 through November 2018, except for the period from September 2014 through June 2015, which was not in the original study period and for which data are also not currently available.[10]

10. The Penney Declaration posits a statistical model (which I will call the "Penney Model") and uses the datasets to estimate the parameters of that model and draw the conclusions described in paragraphs 10, 11, and 58 of the Penney Declaration. The Penney Model posits a straight-line trend in page views for each month from January 2012 through May 2013; an immediate change in June 2013; and a second straight-line trend for each month

[3] Penney Declaration, paragraph 10.

[4] Penney Declaration, paragraph 31.

[5] Penney Declaration, paragraph 34.

[6] In the Terror 48 dataset provided as support for the Penney Declaration, the articles "Recruitment" and "Fundamentalism" have exactly the same number of page views in 30 of the 32 months, and therefore I concluded that Penney made a copy/paste error with respect to this data. The inclusion of this error in the analyses makes little difference for the first 32 months, but in comparing page views for the more recent time period where I supplemented the data, I could not determine whether the data for the original 32 months should have been associated with Recruitment or Fundamentalism and therefore I exclude both where noted.

[7] Penney Declaration, paragraph 48. According to the Penney Declaration, the so-called high privacy articles were determined using a survey conducted via an online survey tool named Mechanical Turk, which I did not evaluate for its accuracy or validity.

[8] Penney Declaration, paragraph 49. The Penney Declaration did not include analyses for the Global 2 dataset but since that dataset was provided to me as part of the data that was considered in the Penney Declaration, I include it in my analyses. The Global 2 apparently includes mobile data whereas the Global 1 dataset does not.

[9] Penney Declaration paragraphs 52-56 describe the Popular, Infrastructure, and Security articles.

[10] If available that data could have been used to provide further insight into trends, but its unavailability is irrelevant to my conclusions.

from June 2013 until August 2014. The hypothesis for the articles in the Terror datasets[11] is that there is a steady increase through May 2013, followed by an immediate decline in June 2013, followed by a steady decline thereafter. Furthermore, the hypothesis for the sets of comparator articles is that they experience neither an immediate decline nor a change in monthly trends in June 2013.[12]

### B. A Simple Review of Article Page Views Indicates That A Decline in Page Views Does Not Begin in June 2013

11. Before reviewing the specific analysis found in the Penney Declaration, I review the page views for the individual 48 terror-related articles (the Terror 48) that the Penney Declaration claims were subject to a chilling effect in June 2013.[13] I find that the page views per article controvert the Penney Declaration conclusion (based on aggregation of the page view data) that there is a rise until May 2013 followed by "statistically significant and substantial drop in view counts immediately following June 2013."[14]

12. My review of the page views for the individual articles shows that almost none of the Terror 48 articles experiences its peak in May 2013 (the hypothesis of the Penney Declaration). For the Terror 48 articles, 17 had already reached their peak number of page views in 2012 and 18 more reached their peak at some point between January and April of 2013. In other words, 35 out of 48 (73%) reached their peak prior to the hypothesized peak of May 2013, and thus the occurrences of June 2013 could not have possibly caused any of these drops in page views. Eleven more of the articles (23%) reached their peak after the disclosures, meaning there was no immediate and sustained drop in June 2013, again controverting the hypothesis in the Penney Declaration. Just two out of 48 (4%) reached their peak in the hypothesized month of May 2013. Even these two articles, though they reached their highest level in May 2013, do not appear to follow the pattern of a steady rise until May 2013 and then a sustained drop afterwards.

13. While many (but not all) of the Terror 48 articles experienced higher numbers of page views in 2012 and early 2013 when compared to late 2013 and early 2014, the decline did not begin in June 2013. Furthermore, the page views did not consistently rise or fall for any sustained period for most articles. To visually demonstrate this fact, I plotted the page views for each of the Terror 48 articles on a single graph. As shown in Figure 1, there is no immediate decline in June 2013, no consistent upward trend through May 2013, and no consistent downward trend that begins in June 2013.

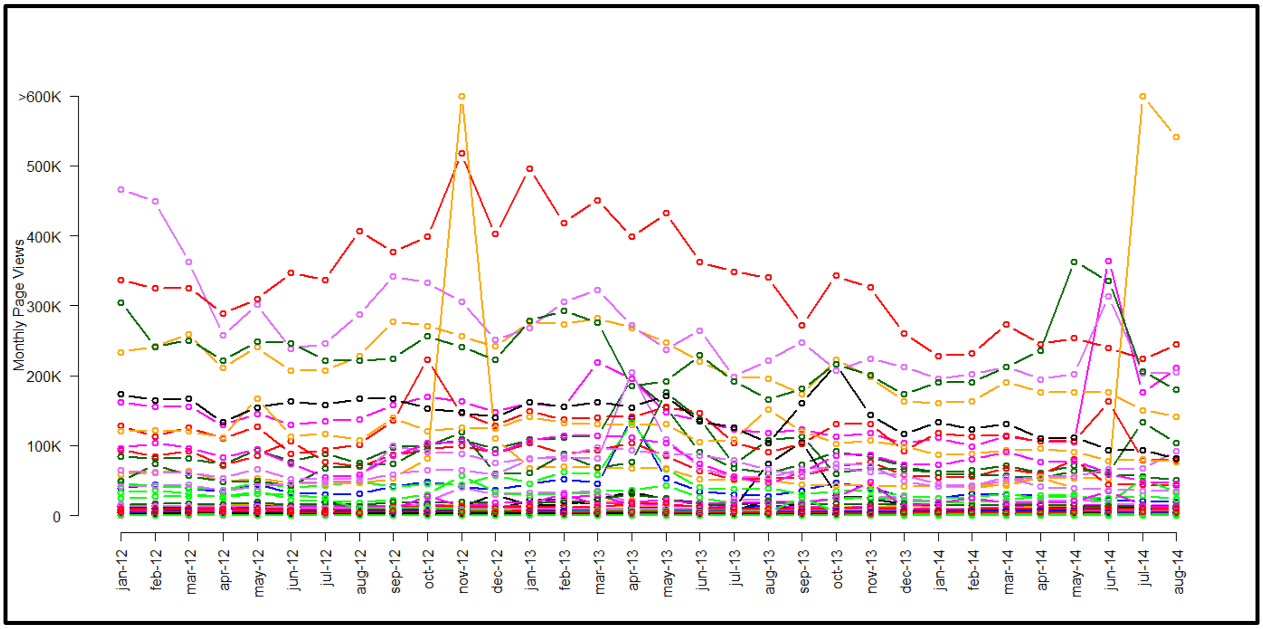
[11] The analysis covers all 48 articles but the conclusions made in the Penney Declaration apply only to 47 (the Terror 48 minus Hamas set of articles) and 31 (the High Privacy 31) of those articles.

[12] See Penney Declaration, paragraph 11.

[13] Technically, the Penney Declaration only makes conclusions regarding the Terror 48 articles without Hamas and the High Privacy 31 articles (see paragraph 58 of the Penney Declaration) but I review all 48 articles here for completeness.

[14] Penney Declaration, paragraph 11. The "trend reversal" referred to in Penney Declaration Paragraph 11 is alluding to a purported rise prior to June 2013 and a drop afterward.

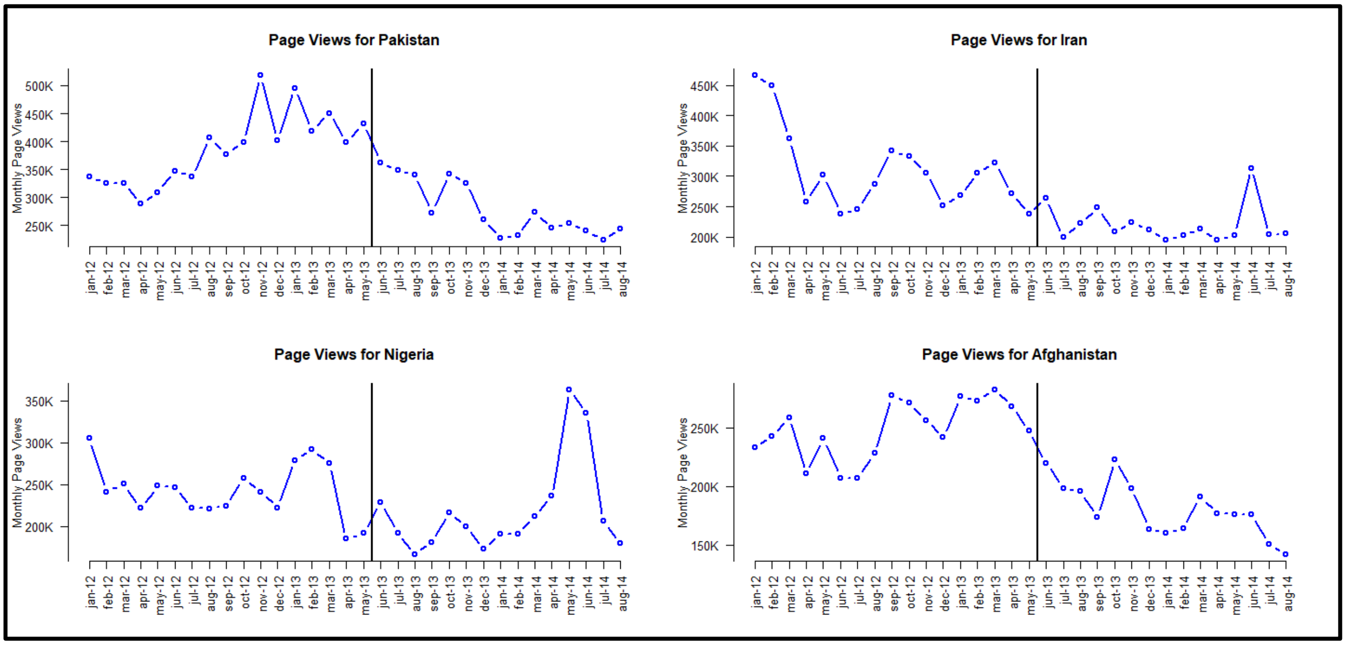
**Figure 1: Individual Page Views for Each of the Articles Within the Terror 48, Which The Penney Declaration Hypothesized Show an Immediate Decline Beginning in June 2013**



14. In short, the Penney Declaration's conclusions are controverted by a simple disaggregated review of the data for each article. The rest of my report carefully reviews the data and the Penney Declaration to explain the reasons for the incorrect conclusions.

15. While Figure 1 is helpful in showing that there is no overall or consistent downward trend starting in June 2013, reviewing the page view data for individual articles allows one to see that none of the articles follows the hypothesis set forth in the Penney Declaration. (I have included page view data for each of the articles in the Terror 48 set in Appendix IV.) For example, Figure 2 below shows the page views for the four articles with the most page views of the Terror 48. As can be seen in these individual graphs, there does appear to be a general decline in page views. However, that decline did not begin with the June 2013 disclosures. Page views for the Pakistan article peaked in 2012, and followed with an erratic decline. Page views for the Iran article saw their peak in January 2012, and erratically declined thereafter. Page views for the Nigeria article were more erratic, with no clear increase or decline. Page views for the Afghanistan article were erratically increasing or remaining about the same until early 2013 when they began to erratically decline.

**Figure 2: Individual Articles show no Association of June 2013 with a Decline in Page Views**



16. These four graphs, above, are indicative of the pages views of all 48 articles in that not one of the 48 articles appears to follow the Penney Declaration hypothesis of a steady increase through May 2013 followed by an immediate drop and steady decline beginning in June 2013. In addition, a review of the entire set of individual graphs by article, which I have provided in Appendix IV, reveals that there are vast differences in monthly page views over time in each article.[15] Given those vast differences, it is not statistically appropriate to combine them for the purposes of analysis, as Dr. Penney did in his analysis.

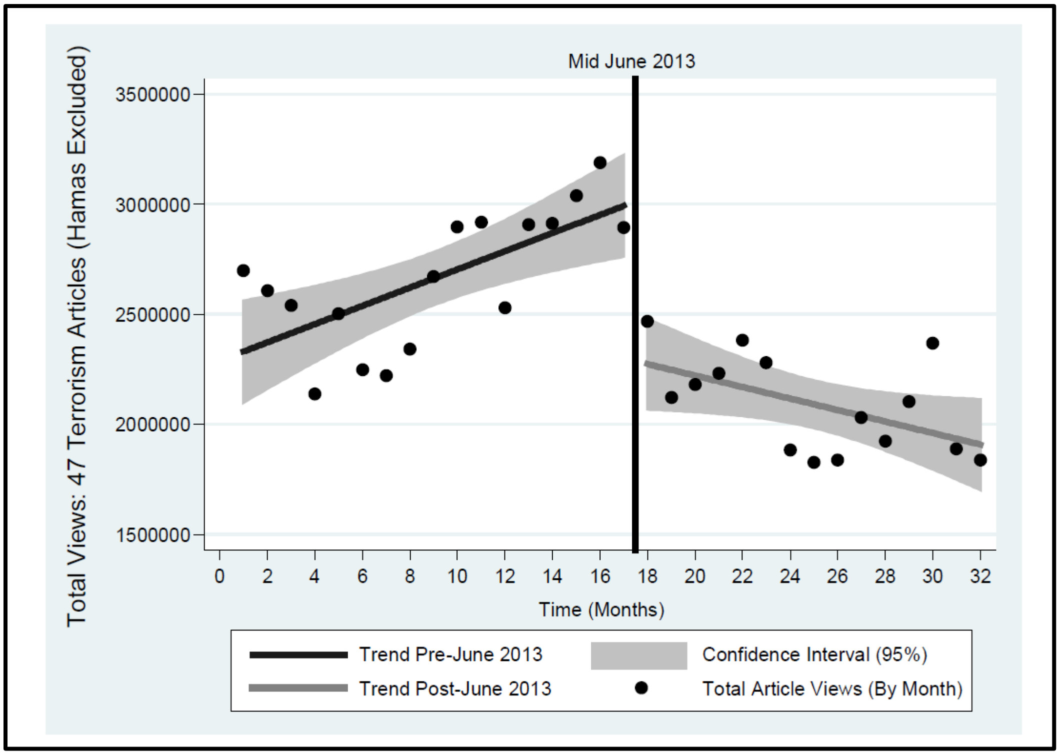
17. As I explain in Section F below, ignoring these differences biases the model and renders it invalid. The simple reason is that such aggregation masks the individual differences in page views. Although aggregation can be appropriate in instances where most of the data tell a consistent and similar story and the aggregation merely eliminates outliers (which would, in that instance, be considered "noise"), where the data are vastly different (as here) aggregation skews the data and tells a misleading story. While I review the aggregate data analyzed in the Penney Declaration in the next section, my review does not imply agreement with the methodology of aggregating the data here.

[15] Note that I scaled each of the 48 graphs according to its page views in order to clearly show the trends. In the aggregate analysis performed in the Penney Declaration, the articles with the most page views are also treated as highly influential because the aggregation of the graphs is influenced according to page view.

### C. The Aggregate Data Analyzed in the Penney Declaration Do Not Indicate Either a Peak in May 2013 or a Long Term Decline Beginning in June 2013

18. I begin my analysis of the aggregated data with an analysis of the Penney Declaration's Figure 2, which shows the Terror 48 without Hamas data set (totaling 47 articles) that were analyzed. A careful view of the Penney Declaration's Figure 2 (reproduced below as my Figure 3) indicates that the peak in monthly page views does not occur in May 2013 and there is no immediate drop or trend reversal in June 2013. In other words, even the aggregated figure presented in the Penney Declaration fails to show the hypothesized trend reversal and drop in June 2013.

**Figure 3: Penny Declaration Figure 2 Reveals Some of the Flaws of the Penney Declaration Analysis**



19. The suggestive trend lines in the Penney Declaration's figure give the impression of a steady increase followed by a decrease, but the points, representing individual months, reveal otherwise. Careful attention to Figure 2 in the Penney Declaration reveals that the page views went up and down several times over the course of the 32 months shown and did not have a single peak in May 2013 (month 17 in the Penney Declaration figure reproduced above).

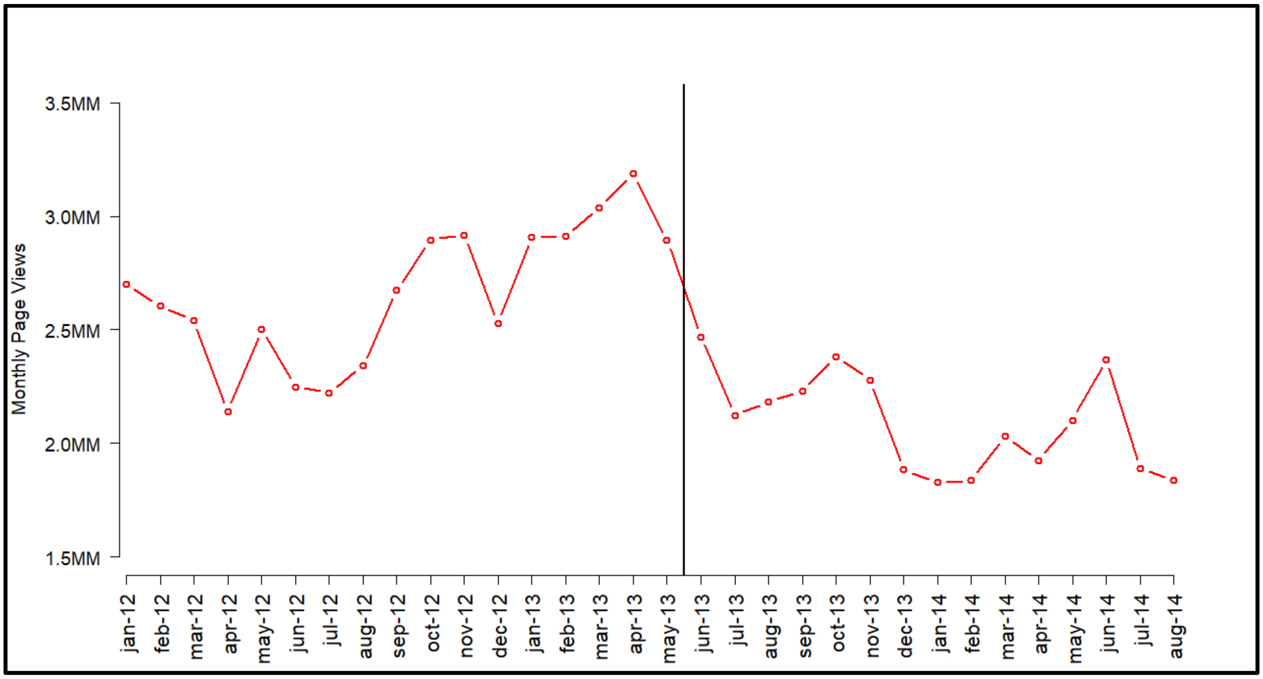
20. Furthermore, only 16 of the 32 months (50%) show page view totals within the model's 95% confidence interval. A properly constructed 95% confidence interval should contain about 95% of the data points. In this instance, the failure to capture a remarkable 50% of

the data points within the 95% confidence interval may be due to an incorrect model, improper construction of the interval, or both.

21. Using the same data points that the Penney Declaration analyzes, I re-drew the Penney Declaration Figure 2 (see Figure 4 below), adding proper labeling of dates and removing suggestive trend lines. In contrast to the solid upward line drawn on the Penney Declaration figure, my plotting of the same points in Figure 4 shows that there are a number of both declines and increases. There is a notable trough in the Summer of 2012, for example, and the number of page views appears to be generally declining through July 2012. Importantly, the highest number of page views occurred in April 2013 and not the hypothesized May 2013.

22. Beyond June 2013, when the Penney Declaration hypothesizes a steady decline, the number of page views go up and down, rising three months in a row from August through October 2013, and again rising three out of four months from March through June 2014.

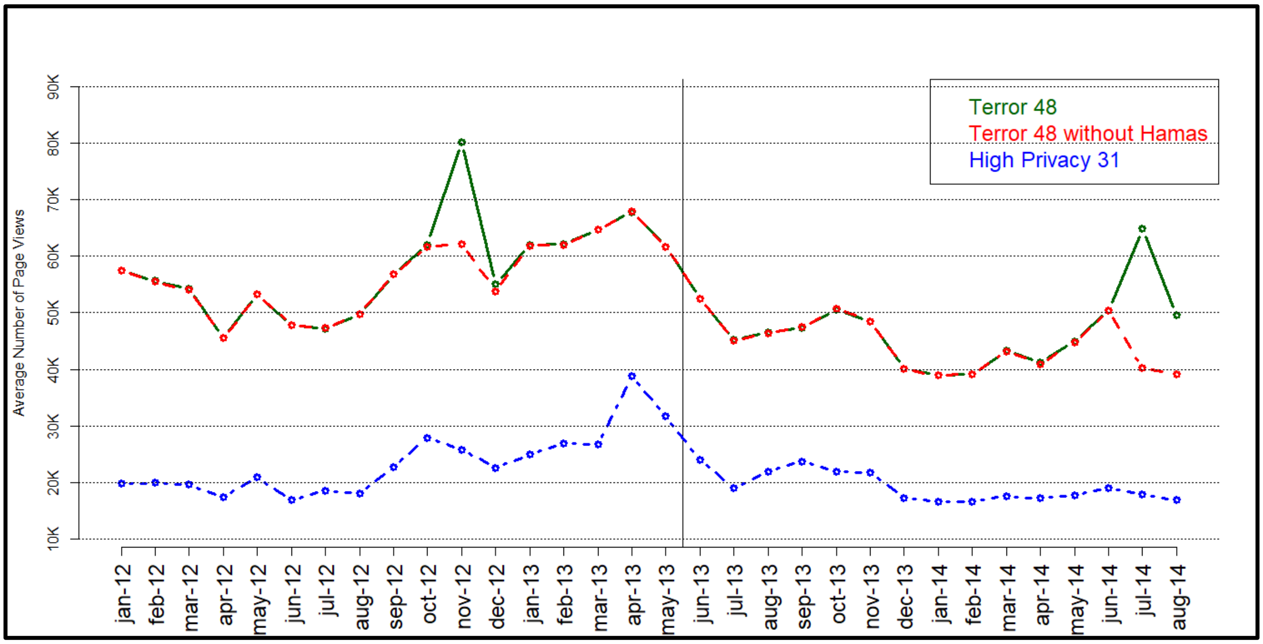
**Figure 4: Terror 48 Without Hamas Dataset Without the Penney Declaration "Trend" Lines**



23. Figure 5 below adds the other two datasets analyzed (Terror 48 and High Privacy 31) to the Terror 48 Without Hamas dataset graphed above, and I used the average page views per article rather than the sum.[16] Once again, Figure 5 indicates that the peak is in April 2013 (and prior to April for the Terror 48 dataset) and that there is no sudden drop in June 2013.

[16] The red line in Figure 4, which shows the total page views for the Terror 48 without Hamas data, has exactly the same pattern as the red line in Figure 5, which shows the average page views for the same data set. The left axis in Figure 5 is just divided by 47 in order to display the average instead of the total.

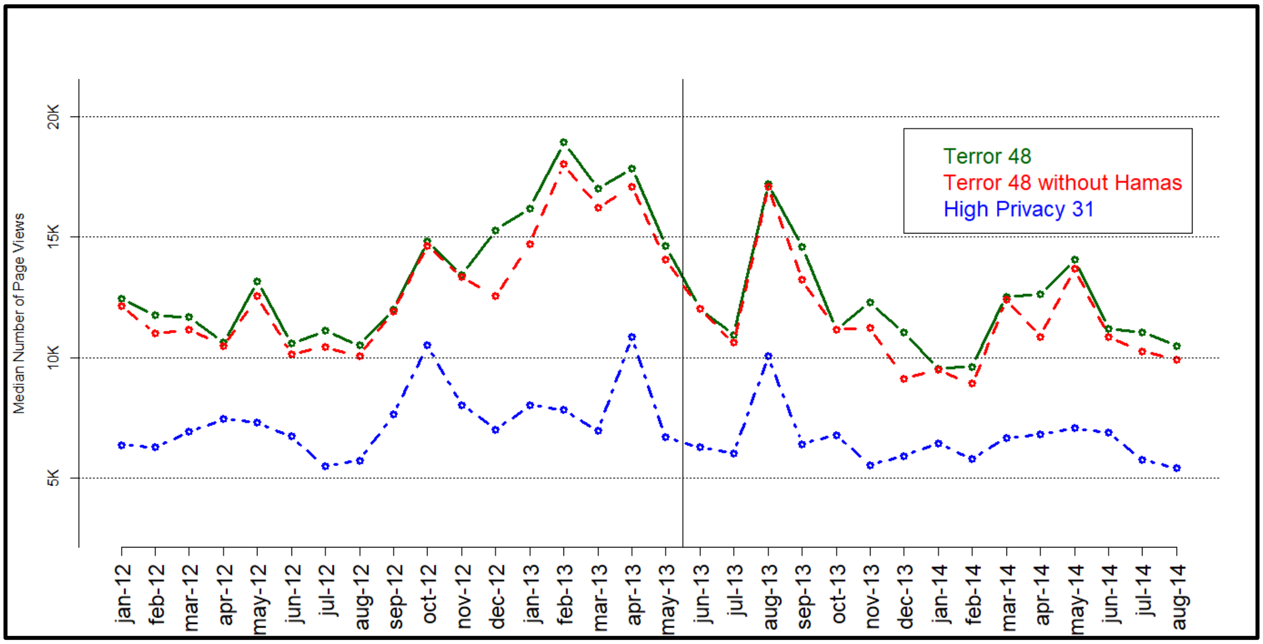
**Figure 5: Average Page Views Show a Peak in April 2013 or Before**



24. Because the average number of monthly page views can be affected by a single article with a very high number of page views in a particular month, I also show the median number of page views by month in Figure 6, below. The median number of page views for any given month is the middle number of page views when the number of views by article is sorted from the lowest number of views to the highest number of views. Therefore, the median shows the number of page views for the "typical" article in the group for a particular month, and therefore is not sensitive to a few articles with very high (or very low) page views for a month. As shown in Figure 6, the peak in median page views occurs prior to the hypothesized peak of May 2013. These data indicate that a rise in page views began in the Summer or Fall of 2012 and peaked in the Winter or Spring of 2013.

25. Figure 6 indicates that while page views generally rose for some time beginning in late 2012, no dramatic peak or fall occurred. Instead, there was a slow and unsteady rise and decline. The page views appear to level off to about early 2012 levels by the Summer of 2014, when the Penney Declaration data end.

**Figure 6: Median Page Views Show a Peak in April 2013 or Before**



26. In summary, based on the individual article data and the aggregated data, the Penney Declaration hypothesis of an increase through May 2013 followed by an immediate and continuing drop afterwards has no support.

## D. Extended Data on Page Views Does Not Indicate an Immediate or Long Term Decline Beginning in June 2013

27. The individual and aggregate article data are very different but they are consistent in that they both show that there was no abrupt and sustained decline in monthly page views beginning in June 2013. The figures and analyses above, like the Penney Declaration, only use page view data through August of 2014. As I explained, I also supplemented that data with publicly available page view data from Wikimedia, by article, for the period July 2015 through November 2018.[17]

28. While I obtained data for each of the original 48 articles, there are inconsistencies or errors associated with five of those articles. Specifically, there were five articles in which the keywords changed, i.e., that the article was under a prior keyword but now a search for that keyword redirects to a different article (e.g., the "terror" article became "fear").[18]

[17] A link to this data ("Hamas" page is shown as an example in this link) is https://tools.wmflabs.org/pageviews/?project=en.wikipedia.org&platform=all-access&agent=user&start=2015-07&end=2018-11&pages=Hamas. The data are taken from en.wikipedia.org, with a selection of monthly data on all platforms with an "Agent" of "user."

[18] The five articles in which key words changed are: 1) "weapons grade" is now "weapons grade nuclear material"; 2) "Euskadi ta Askatasuna" is now "ETA (separatist group)"; 3) "pirates" is now "piracy"; 4) "Islamist" is now "Islamism"; and 5) "terror" is now "fear". The article "title" and "keyword" were synonymous prior to the changes (i.e., when a user entered the keyword into Wikipedia's search tool, they were directed to an article of the same name). After the changes, entering the keyword into the search tool directs you to the new article. When I gathered the page view information the keyword terror redirected to an article titled fear, for example. I note that now, on

In addition, I noticed that the data for two other articles containing the keywords recruitment and fundamentalism were exactly the same in the dataset provided along with the Penney Declaration in all but two months. This apparent error in the Penney Declaration data affects comparisons of those keywords with their correctly downloaded page views from 2015 through 2018. Because of the inconsistencies and errors for these seven articles' data, I include these in some analyses and exclude them in others. Their inclusion or exclusion does not change my conclusions.

29. In summary, I created a dataset for all 48 articles from January 2012 through November 2018, excluding September 2014 through June 2015 because Wikimedia does not make the data for those months available. Since there are five articles with differing key words and the two articles with potential data errors, I exclude those seven of the 48 articles from sets (b), (c), and (d), identified below. In short, when presenting the data for the entire 2012-2018 period, I use four datasets analogous to the terror datasets used in the Penney Declaration to examine page views for the 2012 to 2014 period, but which take into account the exclusion of data from the seven articles with anomalies:

   a. Page views for the 48 terror-related articles, which as noted above I call the "Terror 48;"

   b. Page views for the Terror 48 without the seven articles that have inconsistencies in data or naming, which I call "Terror 41;"

   c. Page views for Terror 41 without the Hamas article, which I call "Terror 41 without Hamas";

   d. Page views for the 26 articles that were included in the 31 "high privacy" in the Penney Declaration and that were also part of the Terror 41 articles. I call these articles "High Privacy 26."[19]

30. The four datasets all show that there was no immediate or long term decline in monthly pages views that began in June 2013. I provide graphs for each of the Terror 48 articles over the extended period in Appendix V, and my earlier conclusion is the same: there is no immediate or long-term drop in any of the individual articles' monthly page views beginning in June 2013.

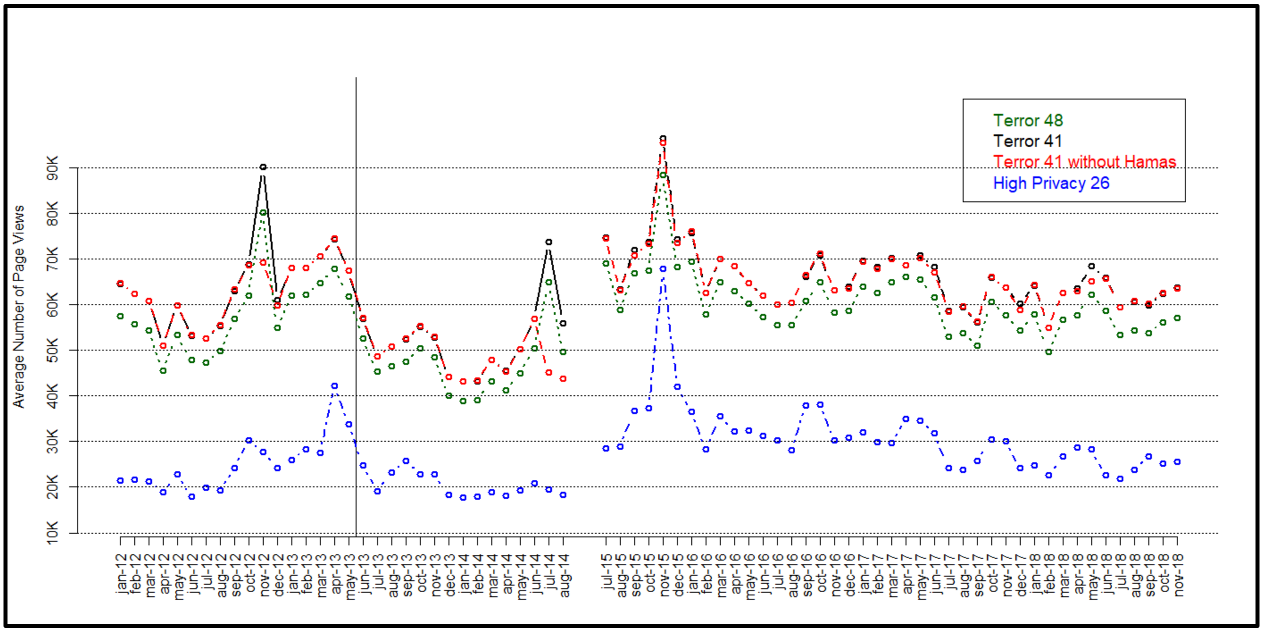
31. I also show the aggregate data over the extended period. Figure 7 below shows the average monthly number of page views for the terror datasets. The later data show many months with average page views in the range of 60,000 to 70,000, about the level of the peak months prior to June 2013. In other words, to the extent that page views did decline in late 2013 and early 2014, that decline appeared to reverse in 2015.[20]

February 14, 2019, terror no longer redirects to fear but instead again goes to a Wikipedia article called "Terror." The other four keywords still redirect as described above (as of February 14, 2019).

[19] The High Privacy 26 contains views for the 31 High Privacy articles after removing the five articles (among the seven articles) that had data issues, *see* above n.18, and were among the 31 High Privacy articles. Those five are Islamist, Recruitment, Weapons Grade, Euskadi ta Askatasuna, and terror.

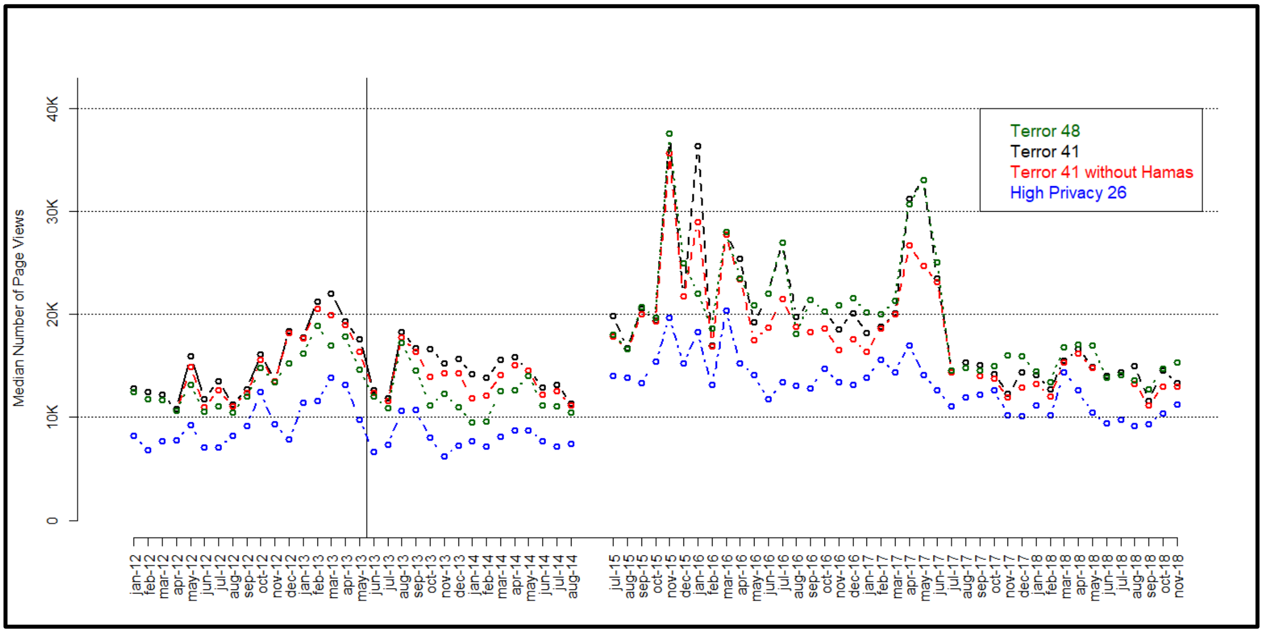
[20] As I will explain further below, the behavior of the aggregate data need not be indicative of the behavior of the individual article data. For example, the aggregate averages have a peak near the November 2015 Paris terror attacks, but that does not mean that all or most of the individual articles peaked around that time.

**Figure 7: Average Page Views for Extended Period (Through November 2018) Fail to Support the Theories in the Penney Declaration**



32. The average number of monthly page views is heavily influenced by the articles with the largest number of views and can be skewed by a single article with heavy readership in a single month. For that reason, I also calculated the median page views by month for the data through November 2018. As shown in Figure 8, median page views in 2015 and beyond often surpassed June 2013 views, a fact that undermines the theory that page views declined and remained low after June 2013.

**Figure 8: Median Page Views for Extended Period (Through November 2018) Undermine the Theories in the Penney Declaration**



## E. The Comparison Datasets used in the Penney Declaration are not Comparable and So Do Not Corroborate Its Conclusions

33. The Penney Declaration bases its conclusions in part on the fact that following May 2013 the page views in the five comparison datasets did not decrease in a similar manner as the page views in the terror datasets.[21] Even assuming the issues with the extended terror-related datasets discussed above did not exist, the conclusion regarding the comparison datasets is flawed because the Penney Declaration does not demonstrate that the comparison datasets were truly comparable.

34. In particular, the Penney Declaration does not demonstrate that the comparison datasets would have had increases and decreases similar to those of the terror datasets *but for* the June 2013 disclosures. There is no analysis in the Penney Declaration that shows that the trends in page views were similar before June 2013 nor does the Penney Declaration explore whether other factors may have changed the trend of the comparison groups in ways that would not have changed the trend of the terror articles.

35. This issue means there is potential bias in any comparisons due to what is called selection by history. In simple terms, this means that if the comparison groups are not similar to the terror datasets to begin with prior to June 2013 (and thus not changing in a similar

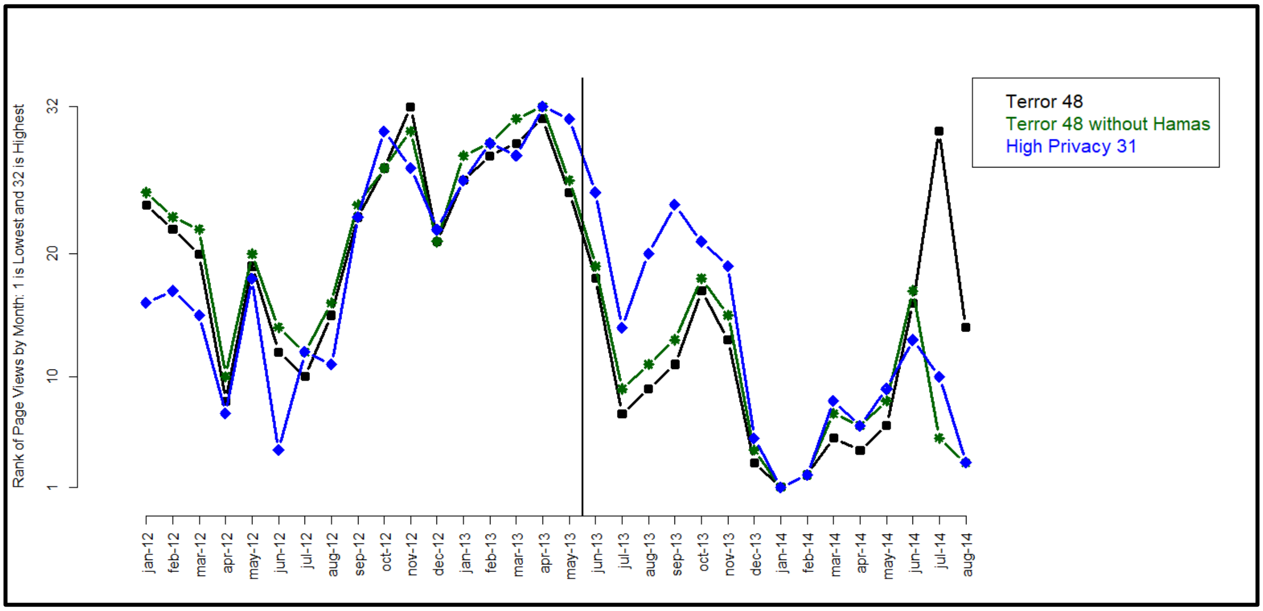
[21] These five datasets consist of "three comparator article groups" cited in paragraph 53 of the Penney Declaration as well as the two global view datasets of Wikipedia home page views used in the Penney Declaration. See my description of these datasets, above, in paragraph 8.

way over time), the estimated effects derived using such comparison groups could be wrong.[22]

36. A simple way to explore whether the terror and comparison datasets are changing in a similar manner prior to the June 2013 disclosures is to review their monthly page views. The magnitude of page views for the five comparison datasets is far different than it is for the terror datasets. Therefore, for each dataset, I ranked the page views by month for each of the 32 months from January 2012 through August 2014. This means that for each dataset, the month with the lowest number of views will have a rank of one, the one with the second lowest will have a rank of two, and so forth, up to the rank of 32, which will be assigned to the month with the highest number of page views.

37. Figure 9 below plots these rankings using the method described in paragraph 37, above, for the following datasets: Terror 48, Terror 48 without Hamas, and High Privacy 31. [23] They are very similar, which is not surprising since two of the three datasets comprise subsets of the articles in the Terror 48 dataset. As shown in the chart, the highest month appears to be either November 2012 or April 2013.

**Figure 9: Ranked Page Views for Terror Articles**



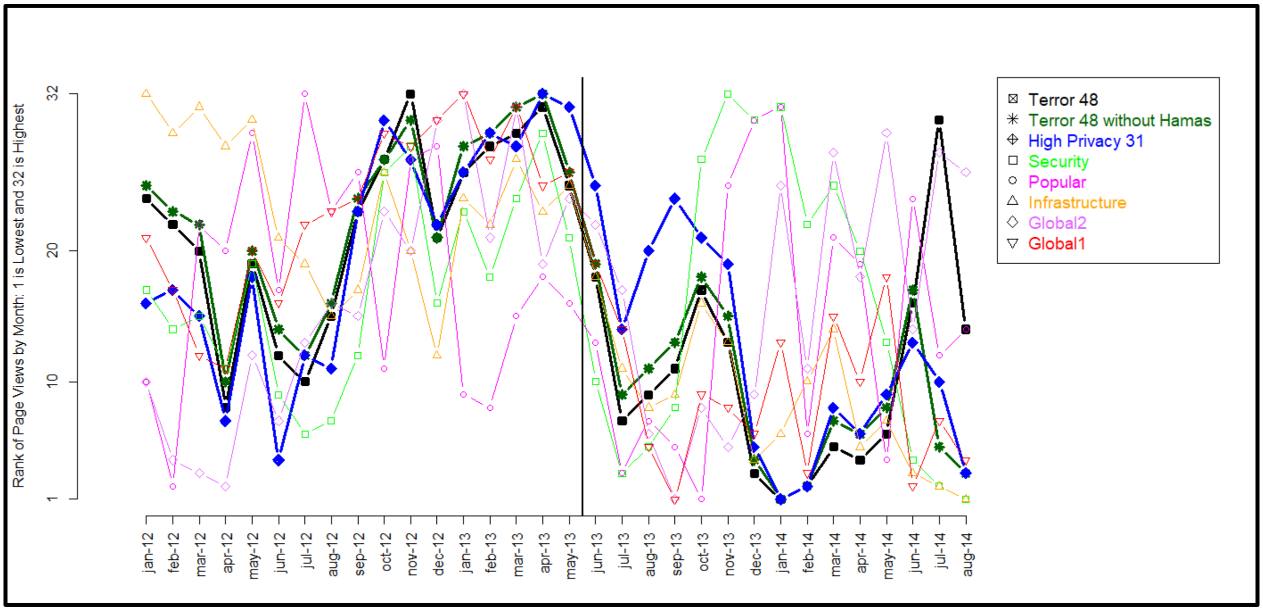
38. Figure 10 below shows the ranked page views for the same three terror datasets along with the five comparison datasets. In order for the comparison between the three terror datasets on one hand and the five comparison datasets on the other hand to be appropriate in determining whether the June 2013 disclosures had a singular effect on the Terror datasets, the trends in page views of the comparison articles would need to be similar prior to June 2013. In other words, a proper control group would roughly follow the

[22] See, for example, "Campbell, Donald, and Stanley, Julian C., Experimental and quasi-experimental Designs for Research, 1963, Houghton-Mifflin, p. 55-57. This issue is also discussed in Salzberg, Alan J., "Removable Selection Bias in Quasi-Experiments," The American Statistician, 1999, pp. 103-107.
[23] See paragraph 7 for detailed descriptions of these datasets.

trend of the Terror articles datasets prior to June 2013, when there is not yet any hypothesized effect. This would mean that a comparison of the data after June 2013 could potentially be used to estimate an effect.

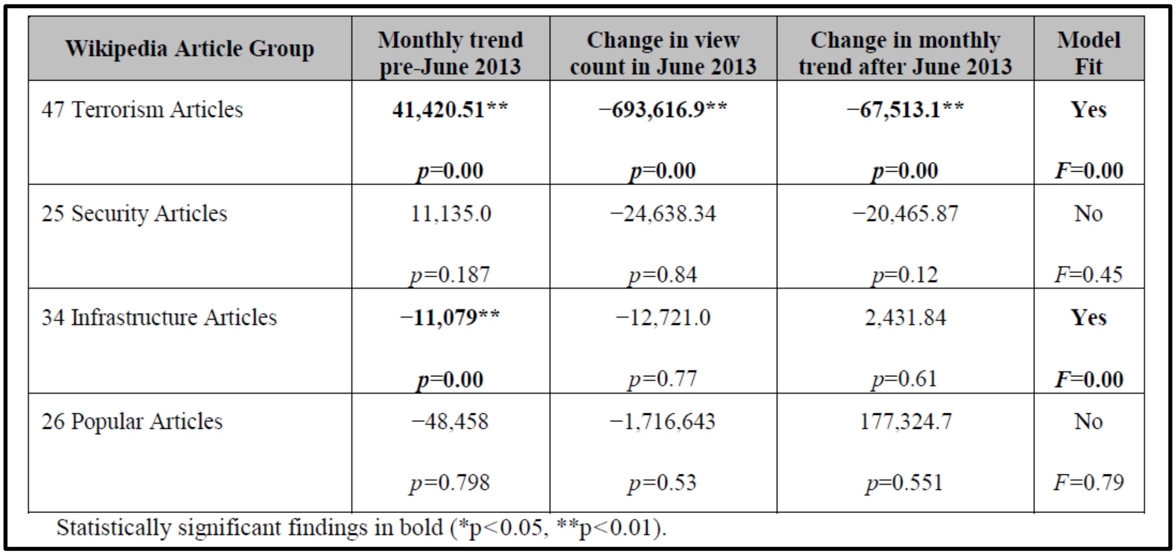
39. Instead, the pre-June 2013 trends of the terror and comparison datasets are not at all alike. Figure 10 shows erratic behavior in the page views for the so-called five comparison datasets prior to June 2013 and that erratic behavior does not mimic the (also) erratic movements in the terror datasets. Therefore, the comparisons made in the Penney Declaration are not appropriate.

**Figure 10: Ranked Views of Terror and Comparison Show Very Different Trends Even Prior to June 2013.**



40. The comparison in Figure 10, which appears to show that the so-called "comparator" groups are not, in fact, comparable prior to June 2013 is confirmed by the Penney Declaration analysis. The Penney Declaration analysis is summarized after paragraph 53 (in Figure 3 of the Penney Declaration), which I have reproduced below as Figure 11.

**Figure 11: Snapshot of Penney Declaration Figure 3**



| Wikipedia Article Group | Monthly trend pre-June 2013 | Change in view count in June 2013 | Change in monthly trend after June 2013 | Model Fit |
|---|---|---|---|---|
| 47 Terrorism Articles | **41,420.51****<br>***p*=0.00** | **−693,616.9****<br>***p*=0.00** | **−67,513.1****<br>***p*=0.00** | **Yes**<br>***F*=0.00** |
| 25 Security Articles | 11,135.0<br>*p*=0.187 | −24,638.34<br>*p*=0.84 | −20,465.87<br>*p*=0.12 | No<br>*F*=0.45 |
| 34 Infrastructure Articles | **−11,079****<br>***p*=0.00** | −12,721.0<br>*p*=0.77 | 2,431.84<br>*p*=0.61 | **Yes**<br>***F*=0.00** |
| 26 Popular Articles | −48,458<br>*p*=0.798 | −1,716,643<br>*p*=0.53 | 177,324.7<br>*p*=0.551 | No<br>*F*=0.79 |

Statistically significant findings in bold (*p<0.05, **p<0.01).

41. The first row of Figure 11 shows the results of the Penney Model for the 47 Terrorism articles. The first column shows a statistically significant upward trend prior to June 2013 for that group. The next row shows the results for the first of the three comparator groups that the Penney Declaration analyzed, the 25 Security articles, and shows no statistically significant trend prior to June 2013. This means that there was no possible reversal that could have occurred around June 2013, making the comparison group of Security articles inappropriate and conclusions based on its use incorrect. The second comparator group, the 34 Infrastructure articles, shown in the third row, shows a statistically significant decline prior to June 2013, indicating that the trend for this comparator group was the opposite of the Terrorism articles and, once again, inappropriate as a comparator group. The final group, of 26 Popular articles, shows no statistically significant trend prior to June 2013, and thus this final group is also inappropriate to use as a comparator group.

42. In summary, none of the three datasets of comparator articles that the Penney Declaration analyzes is an appropriate comparator because none of them exhibits the trend prior to June 2013 that the Penney Declaration posits is indicated by the aggregated data of the Terrorism articles.

43. The Penney Declaration also considers two other datasets, one of global Wikipedia homepage views and one of the same data without mobile data.[24] Both of these datasets show an increase through June 2013 followed by a decline after June 2013.[25] In other words, the Penney Model finds an effect at June 2013 for these two comparison datasets even though his theory is that the page views for these two comparison datasets should not have been affected by the June 2013 disclosures. The Penney Declaration attempts to explain away or minimize this effect by explaining that the effect is smaller for global

[24] These are the datasets identified as Global 1 and Global 2 in paragraph 8, above.

[25] Both show an upward trend prior to June 2013. One shows both the immediate and trend change to be statistically significant and one shows only the immediate change to be statistically significant.

views.[26] However, like the three other comparator datasets, the trend prior to June 2013 is also different for these comparator datasets, and thus there is no reason to expect the trend or immediate change would be the same after June 2013. In other words, these datasets are also poor and inappropriate controls.

44. Furthermore, like the page views for the terror-related articles, the page views for the comparison articles vary substantially from one another, not simply in overall number of views but importantly in their trends over time. Graphs of page views for each article used in the comparison datasets, which I provide in Appendix VII, clearly show that among the control articles trends in page views are vastly different. In other words, to the extent that some of the controls might be appropriate, they would need to be used individually (and not in aggregate) and individual factors affecting page views would need to be accounted for, as I explain below.

45. As with the terror-related articles, and as I will explain in detail in the following section, the Penney Model is a flawed and oversimplified model that does not account for any individual differences in page views, and instead assumes the only differences and changes are due to the June 2013 disclosures.

46. In summary, the five comparator datasets used in the Penney Declaration do not support the Penney Declaration conclusions. The three datasets of article page views all have different trends prior to the June 2013 disclosures, making them inappropriate for comparison. The two Wikipedia homepage datasets have a statistically significant trend upward prior to June 2013, but the peak occurs prior to May 2013 and does not correspond to the trend in the terror article views prior to June 2013. This fact means these articles are also not appropriate controls.

### F. The Penney Model Estimates are Deeply Flawed, Inappropriate and Likely Biased

47. As explained above, there is no indication of either an abrupt drop in monthly page views of the terror-related articles or an abrupt reversal in an upward trend in views of such articles beginning in June 2013. However, two of the Penney Model estimates are statistically significant, and this statistical significance forms the basis for the Penney Declaration's conclusions.[27] How is it, then, that a simple examination of the data shows no abrupt change or reversal, but two of the Penney Model estimates show a statistically significant change and reversal? The reason is that a deeply flawed model gives deeply flawed results. Because the Penney Model divides the data around an assumed inflection point, it forces the assumption that all changes in page views, beyond a simple trend line, that occurred after that point are caused by the June 2013 disclosures. This flawed assumption drives the spurious statistical significance and other incorrect results. I explain the flaws of the Penney Model in detail below.

48. **The first flaw** in the Penney Model is that the model aggregates the data, and this aggregation masks the differences in the changes in views over time by article. The

[26] As with the terror datasets, the decline actually begins *before* the hypothesized month of June 2013.

[27] Penney Declaration, paragraph 11.

Penney Declaration did not explore whether the claimed reversal in trend existed for each article, and did not explore whether it occurred at the same time, if it occurred at all. Review of the simple graphs of each of the Terror 48 articles, which I provide in Appendix IV (I show four of them in Figure 2), clearly indicates that the trend of page views and their changes over time are not the same for each article. This means that aggregating the data for a single model is inappropriate.

49. As explained earlier, only 2 of the 48 articles' page views peak as hypothesized (in May 2013). Thirty-five of 48 (73%) reach their page view peak earlier than May. In other words the steady march upward followed by an abrupt drop in June 2013 and a steady march downward is a fiction created partly by aggregation of the data.

50. This aggregation is performed without any analysis of the individual datasets to determine whether such aggregation is appropriate. The page views for the 48 articles is an example of what is called "panel data" (in this case the 32 months of page views for each article consists of a panel). Because each of the panels may be different over time, and the panels may be related to one another, a statistical analysis that lumps them together can produce spurious results, as it does in this case.[28] A proper analysis could have used the data for the 48 articles and accounted for the potential effects of specific news events and other influences on each article's page views. There are standard methods for analyzing this kind of panel data but the Penney Model ignores them. [29] Furthermore, as explained in the next paragraphs, even ignoring the differences in the articles and aggregating the data, there is still no indication that the peak is in the hypothesized month of May 2013.

51. **The second flaw** is that the Penney Model assumes a single peak in May 2013 rather than letting the data reveal where, if anywhere, a peak in the data exists.[30] In other words, the Penney Model does not allow for a test of the timing of the change in page views but instead simply assumes that the one and only trend change occurred in June 2013. As a result, the regression model will detect an effect in June 2013 if the period prior to June 2013 generally had increasing page views and the period after generally had declining views, regardless of when the change actually began. That is, even if the change in trend and the decline began *before* the June 2013 disclosures (as it did for 73% of the subject articles, see paragraph 12, above), the Penney Model will find that the disclosures caused them.

52. This model deficiency explains why, despite the aggregate data hitting a peak in April 2013 and not the hypothesized May 2013, the Penney Model indicates the peak was in May 2013 (and the trend reversed starting in June 2013). If I alter the Penney Model to check for an April peak (and a reversal of trend in May instead of June), the altered model "proves" the April peak and trend reversal in May.[31] Thus, for example, the

[28] Certain events may cause a change to multiple articles. For example, the rise in views for both "Jihad" and "ammonium nitrate" occurred at the time of the Boston bombings, as I detail below.

[29] For example, see Wooldridge, Jeffrey M., Introductory Econometrics, A Modern Approach, 5th Edition, 2012, South-Western Cengage Learning, p. 459-474.

[30] The model also does not allow for there to be multiple peaks in the data.

[31] This is also true when checking for trend reversal in April 2013. The output from these alternative models is contained in the appendix. I do not consider the Penney Model or any of these models appropriate, because they do

alternate (and opposing) theory that the Boston Marathon bombings (which occurred in April 2013) caused the trend reversal beginning in May is also "proven" using the Penney Model.

53. A simple method of checking for the timing of a reversal is possible using what is called a polynomial model. Such a method is common for determining whether and when a trend changes direction (from increasing to decreasing and vice-versa). For reasons outlined below, this simple model, like the Penney Model, is far from adequate and does little to account for the changes in page views.[32] I simply use it to demonstrate that had the Penney Declaration estimated the timing of the reversal in trend in aggregate page views in even this simple fashion, it would not have found that it occurred beginning in June 2013.

54. A polynomial model estimates that views of the Terror 48 article peaked in September 2012; that views of the Terror 48 without Hamas article peaked in November 2012; and that views of the Terror 31 articles peaked in March of 2013. In other words, contrary to the Penney Declaration theory, a model that is forced to select a single peak does not estimate that peak to be the month hypothesized by the Penney Model.

55. **The third flaw** is that the Penney Model is oversimplified, leaving out virtually all factors that could affect page views of terror-related articles from the model. The only factors in the model are a simple trend over time and a single hypothesized cause for the change in June 2013. This means that to the extent that page views change due to factors other than the June 2013 disclosures, those unidentified factors and their concomitant effects on page views will be inappropriately incorporated into the estimates of trend reversal. For example, the Penney Model fails to account for seasonality or major news events that may have affected page views.[33]

56. Such an over-simplified model suffers from what is called "omitted variable bias" and means that the conclusions may be wrong because estimates from the model are biased.[34] This problem means the true effect of the June 2013 disclosures may be non-existent or in the opposite direction of the effect as estimated by the flawed model.[35]

not account for seasonality or any other factors (as I explain later). However, the fact that a statistically significant trend reversal can also be found in April and May indicates that the hypothesis that such a change occurred specifically in June 2013 is in no way proven by the Penney Model, even if one assumes that a model with a single change in trend is correct.

[32] For example, it only allows for one change in trend and it does not allow for any effects due to things like world events relevant to individual articles (except for those related to the Hamas article) or seasonality, *see* paragraphs 56-61, below.

[33] Although the Penney Declaration correctly states (in paragraph 26) that the time period is long enough that one could control for seasonality (e.g., lower page views in the summer than at other times of the year), it is barely so, and in any case the Penney Model does not actually attempt to account for any seasonality. This means that the differing number of summer and winter months in the pre-June 2013 and post-June 2013 analysis will affect the results, for example. For some of the regressions, the Penney Model controls what is called "first-order serial autocorrelation," but this correction does not address seasonality.

[34] See, for example, Wooldridge, Jeffrey M., Introductory Econometrics, A Modern Approach, 5th Edition, South-Western Cengage Learning, p. 88-91.

[35] For an example of this, see Gujarati, Damodar N., Basic Econometrics, 3rd Edition, McGraw-Hill, 1995, p. 204-207.

57. To demonstrate that there are changes that are not accounted for in the model, I determined if page views dropped during the summer months. In order to check this, I used data from all 48 articles. Therefore, I had a total 1,536 data points, consisting of 32 months, from January 2012 to August 2014, for each article multiplied by 48 articles. The results of my analysis indicate a large and statistically significant reduction in page views in the summer months.[36]

58. Because six of the 15 months considered in Penney's Model are summer months in the period after May 2013 (June 2013 through August 2014), but only three of 17 months are summer months in the period considered before June 2013 (January 2012 through May 2013), a failure to account for the reduction of page views in the summer months means the estimate of an immediate drop and reversal in trend will be overstated in a model like the Penney Model that does not take season into account. As I stated above, the seasonality effect is just one example of a factor that is not accounted for in the Penney Model and is not meant to be exhaustive of the many potential model omissions.

59. The Penney Declaration tacitly acknowledges the fact that it mostly ignores factors affecting page views by excluding the Hamas article from some of its analysis. The reason given for excluding Hamas is that conflicts with Israel occurred in two of the months at-issue and greatly changed page views.[37] While this logically makes sense, the model made no adjustments for any of the other world events occurring during the period of study. The exclusion of the Hamas articles manipulates the data in a way that is favorable to the hypothesis in the Penney Declaration without apparently considering items that may not be favorable.

60. For example, the Boston Marathon bombing occurred two months before the Snowden disclosures, and there was a substantial increase in page views for certain articles. Page views for "Jihad" more than doubled between April and May 2013, from below 100,000 views to above 200,000 views, and page views for Ammonium nitrate (the chemical compound reportedly used in the bomb) had similarly dramatic changes. These dramatic changes corresponding to the Boston bombings were short-term, and, within a month or two, the number of views dropped. Because the Boston bombings occurred prior to June 2013 and are otherwise not accounted for, the increase in page views around April 2013 is improperly incorporated into the estimated "chilling effect" of the June 2013 disclosures by the Penney Model.

61. **The fourth flaw** in the Penney Model is that the 48 terror articles were chosen by Dr. Penney based on their use of terms contained on a 2011 Department of Homeland Security list of terrorism-related terms, and the Model did not take into account that a natural rise or decline in user interest in the topics covered by those articles may occur over time. This could mean that some articles and topics have become less important

[36] Results are in the attached programming log. In order to allow the articles to be comparable despite having different page views, I ranked each article's monthly page views from 1 (lowest) to 32 (highest) prior to performing my analysis. Note that these results do not take into account other factors and therefore the decline in the summer months may be due to particular news events that did or did not occur during those months, for example.

[37] See paragraph 42 of the Penney Declaration.

over time, which could account for a decrease in the number of page views. Also, public interest could shift to newer topics or articles regarding terrorism.

62. I note that while the top few articles in terms of page views were articles about countries, none of the articles in the Terror 48 dataset was about Syria, whose civil war has had an increased news profile over the years. Page views on the article for Syria have averaged nearly 300,000 per month since July 2015, a higher number of views than 47 of the 48 articles explored in the study.[38]

63. Articles about Al Qaeda were included but articles about the Islamic State (including ISIS and ISIL) were not included among the terrorism-related articles considered in the Penney Model. Page views for ISIL (Islamic State of Iraq and the Levant) have averaged more than 600,000 per month since July 2015, higher than any of the 48 articles explored in the Penney Declaration.[39] In short, topics identified in a 2011 list of terrorism related keywords do not necessarily correspond to highly viewed terrorism-related articles during the period of the study or thereafter, and a decline of any static list of articles over time may be expected as "hot" topics change over time.

64. A dramatic demonstration of this issue is the article "Deaths in 2012," which is one of the popular articles used as a control in the Penney Declaration.[40] The page views for this article hovers around 2 million from January through December of 2012 and then quickly drop to nearly zero (for a graph of page views of this article, see Appendix VI). While not necessarily behaving as dramatically as page views for this article, many of the 2011 terrorism-related keywords undoubtably became stale over time, and, subsequently, page views dropped. Such declines have nothing to do with the June 2013 disclosures but are deemed an effect of the June 2013 disclosures by the Penney Model.

65. **The fifth flaw** in the Penney Model relates to the data examined. The data examined only include the 32 months through August of 2014. There is no analysis of any data beyond that date. Therefore, the Penney Model results do not and cannot imply that an effect of the June 2013 disclosures persists today, or did so even in 2015. As I explain above, my own analysis of more recent data shows that page views of the Terror 48 articles are not substantially different than they were prior to June 2013. In addition, changes in the focus of terrorism would mean that some of the articles are less relevant and other articles, not examined at all, are more relevant to the question of whether the Upstream program has a continued chilling effect. This is left unexamined in the Penney Declaration.

66. **The sixth flaw** in the Penney Model is that it fails to isolate the particular effect of public "awareness" about the NSA Upstream program challenged in this suit from the potential effects of, e.g., a) Snowden disclosures about other NSA surveillance activities; b) possible inaccuracies, if any, reported about the Upstream program in the press; c) the Snowden disclosures about British intelligence activities; and d) other events of June

[38] Page views found at https://tools.wmflabs.org/pageviews/?project=en.wikipedia.org&platform=all-access&agent=user&start=2015-07&end=2018-11&pages=Syria.

[39] See https://tools.wmflabs.org/pageviews/?project=en.wikipedia.org&platform=all-access&agent=user&start=2015-07&end=2018-11&pages=Islamic_State_of_Iraq_and_the_Levant .

[40] Penney Declaration, Table 16.

2013. In other words, even if we accept the claim that a chilling effect occurred in June 2013 (and there is no evidence of such an effect), there are no data or statistical analysis offered that indicate such an effect was due to awareness of the specific NSA program at issue here rather than other related or unrelated events of June 2013.

## V. Conclusions

67. The Penney Declaration hypothesizes that a chilling effect from the Snowden disclosures caused page views of certain terrorism-related[41] Wikipedia articles to decline beginning in June 2013 and concludes that the Penney Model results regarding page views of these articles are evidence of the decline.

68. My analysis of those articles shows that the Penney Declaration conclusion is wrong. The mistaken conclusion can be observed by performing a simple analysis of the articles' page views and observing that a decline in page views, when it occurred, generally occurred before the disclosures and almost never occurred beginning in the hypothesized month of June 2013. This fact is seen in both the individual and aggregate data.

69. Comparison datasets that are used as controls in the Penney Declaration display different trends prior to 2013, and therefore are inappropriate as control data. Furthermore, as with the terrorism-related articles, the Penney Model inappropriately aggregates articles that have different trends in these comparison datasets.

70. Even assuming that page views of terrorism-related articles fell, as hypothesized, in the data analyzed, the Penney Declaration analyzes data only through August of 2014. Additional data I analyzed, which run through November 2018, indicate that any declines, which in any case began before June 2013, were relatively short-lived.

71. At the root of the mistaken conclusion in the Penney Declaration is a deeply flawed model that aggregates the data and ignores every possible reason for changes in page views except the June 2013 disclosures that concerned Upstream. This means that all changes in page views are presumed to be part of the effects of the disclosures by the Penney Model, no matter what the underlying reason for the page view changes.

I declare under penalty of perjury that the foregoing is true and correct to the best of my knowledge and belief.

Executed in New York, New York, on February 14, 2019.

Alan J Salzberg

Alan J. Salzberg

[41] Penney Declaration, paragraph 31.

## APPENDIX I: Programming Code

The following is a Stata (Version 14) program and log, used to analyze the data.

**This is the program:**

```
clear
capture log close
log using readandreplicate_20190115.log, replace
use Penney_regression_data.dta

* note that for July 2015 and beyond:
* terror - now fear
* weapons grade is - now weapons grade nuclear material but didnt exist until
June 2017 even as weapons gade nuclear maerials
* Euskadi ta Askatasuna - now ETA (separatist group)
* pirates is - now piracy
* islamist is - now islamism
* recruitment and fundmanetalism have same data in all but 2 of first 32
months--a clear error

*
rename date viewsdate
rename time monthindex
gen date1=date(viewsdate,"MDY")
format date1 %d
gen month1=month(date1)
gen year1=year(date1)
*
* rename for shorter names
rename terrorarticles48 art_Terror_48
rename terrorarticles47 art_Terror_47
rename globalmilnonmobileraw art_Global1
rename terror31higherprivacy  art_Terror_31
rename securityarticles25comparator  art_Security
rename populararticlescomparator  art_Popular
rename infrastructurecomparatorfinal art_Infrastructure
rename globalviewsmilcombined  art_Global2
*
* now index by pct change from median
* and replicate original regressions
foreach var1 of varlist art_*  {
* egen rk_`var1' = rank(`var1')
display "========="
display "`var1'"
display "==========="
regress `var1' monthindex intervention postslope
}
* table 8 replication
regress art_Terror_31 monthindex intervention postslope art_Global1
```

```
* table 9 replication
regress art_Terror_47 monthindex intervention postslope art_Global1
* control regs
regress art_Global2 monthindex intervention postslope

* show that may and april also stat signif
gen interventionmay=intervention
replace interventionmay=1 if monthindex==17
gen postslopemay=postslope
replace postslopemay=postslope+1 if interventionmay==1
gen interventionapril=interventionmay
replace interventionapril=1 if monthindex==16
gen postslopeapril=postslopemay
replace postslopeapril=postslopeapril + 1 if interventionapril==1
list monthindex postslope postslopeapril postslopemay intervention
interventionapril interventionmay
*
* estimate turning point (estimated peak of data)
gen idx2=monthindex^2
regress art_Terror_48 monthindex idx2
predict tmp48
egen max48=max(tmp48)
list viewsdate monthindex if tmp48==max48

regress art_Terror_47 monthindex idx2
predict tmp47
egen max47=max(tmp47)
list viewsdate monthindex if tmp47==max47

regress art_Terror_31 monthindex idx2
predict tmp31
egen max31=max(tmp31)
list viewsdate monthindex if tmp31==max31

drop tmp31 tmp47 tmp48 max31 max47 max48

*
regress art_Terror_31 monthindex intervention postslope
regress art_Terror_31 monthindex interventionmay postslopemay
regress art_Terror_31 monthindex interventionapril postslopeapril

regress art_Terror_47 monthindex intervention postslope
regress art_Terror_47 monthindex interventionmay postslopemay
regress art_Terror_47 monthindex interventionapril postslopeapril

regress art_Terror_47 monthindex intervention postslope
regress art_Terror_47 monthindex interventionmay postslopemay
regress art_Terror_47 monthindex interventionapril postslopeapril
```

```
reshape long art_, i( monthindex date1 month1 year1 intervention postslope)
j(artnmshort) string
rename art_ pageviews
format pageviews %12.0f
egen rankviews=rank(pageviews), by(artnmshort)
 gen yearmonth1=year*100+month1
* most groups peaked in earlier period (not unique to terror articles) and no
group peaked in May 2013 (just before claimed intervention)
list year1 month1 artnmshort if rankviews==32
* trough
list year1 month1 artnmshort if rankviews==1

*
* write out to csv file in order to produce graphs
outsheet using articlesaggregate.csv, comma replace

*****************************
* replicate control regressions
*****************************
clear
use security25
regress sum_view monthindex postslope intervention
outsheet using security25.csv, comma replace

use  infrastructure34
regress sum_view monthindex postslope intervention
outsheet using infrastructure34.csv, comma replace

use popular26
regress sum_view monthindex postslope intervention
outsheet using popular26.csv, comma replace

clear

*******************************
* now use with individual 48
*******************************
clear
use artterror48_origplusrecentdates.dta
gen date1=date(dateorig,"MDY")
gen month1=month(date1)
gen year1=year(date1)
sort date1
gen monthindex=_n
* account for skipped 11 months
replace monthindex = monthindex + 10 if year>=2015
gen intervention=1
replace intervention=0 if date1<date("06/01/2013","MDY")
gen postslope = (monthindex-17)*intervention
```

```
egen totview=rowtotal(art_t*)

* check first regression again
regress totview monthindex postslope intervention if year<=2014
gen totviewminushamas=totview - art_t22
gen totviewminusdup=totview - art_t47
regress totviewminushamas monthindex postslope intervention if year1<=2014
*
regress totviewminusdup monthindex postslope intervention if year1<=2014

*
* now drop totals and reshape
drop totv*
* obvious error in articles on Recruitment and fundamentalism (all numbers
but last couple are the same)
count if art_t46==art_t47

reshape long art_t, i( monthindex date1 month1 year1 intervention postslope)
j(artnum)
*
rename art_t pageviews

* pull in article names
sort artnum
merge m:1 artnum using articlenames48
assert _merge==3
drop _merge
* normalize names for better display and read/write
replace artnames=subinstr(artnames,"(","_",.)
replace artnames=subinstr(artnames,")","_",.)
replace artnames=subinstr(artnames," ","_",.)
replace artnames=subinstr(artnames,"+","_",.)
replace artnames=subinstr(artnames,"-","_",.)
replace artnames=subinstr(artnames,"__","_",.)
replace artnames=subinstr(artnames,"__","_",.)
replace artnames=subinstr(artnames,"__","_",.)

* pull in indicator of whether article was high privacy
sort artnum
merge m:1 artnum using highprivacy31
gen highprivind=_merge==3
assert _merge!=2
drop _merge
*
* indicate 7 articles with issues between early and late period
gen lateissueind=0
replace lateissueind=1 if artname=="terror"
replace lateissueind=1 if artname=="Weapons_grade"
replace lateissueind=1 if artname=="_Euskadi_ta_Askatasuna"
replace lateissueind=1 if artname=="Pirates"
replace lateissueind=1 if artname=="Islamist"
replace lateissueind=1 if artname=="Recruitment"
replace lateissueind=1 if artname=="Fundamentalism"



* check that high privacy desig is ok by checking reg of sum
egen totview31=sum(pageviews), by(monthindex highprivind)
replace totview31=. if highprivind==0
bysort monthindex highprivind: gen tmpindx=_n
regress totview31 monthindex postslope intervention if tmpindx==1 &
year1<=2014
drop tmpindx
*
* get ranks of first 17, first 32 and all
gen pageviewall=pageviews
gen pageviews17=pageviews
replace pageviews=. if year>2014
replace pageviews17=. if monthindex>=18
egen rankviewsearly=rank(pageviews), by(artnum)
egen maxrankearly=max(rankviewsearly), by(artnum)
egen rankviews17=rank(pageviews17), by(artnum)
egen maxrank17=max(rankviews17), by(artnum)
egen rankviewsall=rank(pageviewall), by(artnum)
egen maxrankall=max(rankviewsall), by(artnum)

sum maxr*
sum rankv*
sort artnum date1

*
gen yearmonth=year1*100 + month1
* summermonths lower in general --inidcation of seasonality
* use rank so all data can be considered on a like to like basis
 table month1, c(mean rankviewsearly median rankviewsearly mean rankviewsall
median rankviewsall n rankviewsall) row format(%6.2f)
 table month1, c(mean rankviewsearly median rankviewsearly mean rankviewsall
median rankviewsall n rankviewsall) row format(%6.2f)
regress rankviewsall i.month1 if lateissueind==0
regress rankviewsall i.month1 if monthindex<=32

 * where is maximum?
 tab yearmonth highpriv  if rankviewsearly==maxrankearly
 tab yearmonth highpriv  if rankviewsall==maxrankall

* output to csv for graphics and other analysis
gen dateformat=date1
format dateformat %d
```

```
outsheet using orig48long.csv, comma replace
*
log close
```

**This is the program log:**

```
       log:
D:\clients_2018\DOJ_Wiki_NSA\programsdata\readandreplicate_20190115.log
  log type:  text
 opened on:  15 Jan 2019, 18:07:38

. use Penney_regression_data.dta


.
. * note that for July 2015 and beyond:
. * terror - now fear
. * weapons grade is - now weapons grade nuclear material but didnt exist
until June 2017 even as weapons gade nuclear maer
> ials
. * Euskadi ta Askatasuna - now ETA (separatist group)
. * pirates is - now piracy
. * islamist is - now islamism
. * recruitment and fundmanetalism have same data in all but 2 of first 32
months--a clear error
.
. *
. rename date viewsdate

. rename time monthindex

. gen date1=date(viewsdate,"MDY")

. format date1 %d

. gen month1=month(date1)

. gen year1=year(date1)

. *
. * rename for shorter names
. rename terrorarticles48 art_Terror_48

. rename terrorarticles47 art_Terror_47

. rename globalmilnonmobileraw art_Global1

. rename terror31higherprivacy  art_Terror_31
. rename securityarticles25comparator  art_Security

. rename populararticlescomparator  art_Popular

. rename infrastructurecomparatorfinal art_Infrastructure

. rename globalviewsmilcombined  art_Global2

. *
. * now index by pct change from median
. * and replicate original regressions
. foreach var1 of varlist art_*  {
  2. * egen rk_`var1' = rank(`var1')
. display "========="
  3. display "`var1'"
  4. display "==========="
  5. regress `var1' monthindex intervention postslope
  6. }
=========
art_Terror_48
===========

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
9.16
       Model |  3.1498e+12         3  1.0499e+12   Prob > F        =
0.0002
    Residual |  3.2091e+12        28  1.1461e+11   R-squared       =
0.4953
-------------+----------------------------------   Adj R-squared   =
0.4413
       Total |  6.3590e+12        31  2.0513e+11   Root MSE        =
3.4e+05

------------------------------------------------------------------------------
-
art_Terro~48 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |   47038.28   16760.41     2.81   0.009     12706.13
81370.43
intervention |  -995085.2   241987.6    -4.11   0.000     -1490774   -
499396.1
   postslope |  -35517.69   26272.41    -1.35   0.187    -89334.29
18298.91
```

```
       _cons |    2352364   171743.1    13.70   0.000      2000564
2704164
------------------------------------------------------------------------------
-
=========
art_Terror_47
===========

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
24.85
       Model |  3.4887e+12         3  1.1629e+12   Prob > F        =
0.0000
    Residual |  1.3105e+12        28  4.6805e+10   R-squared       =
0.7269
-------------+----------------------------------   Adj R-squared   =
0.6977
       Total |  4.7992e+12        31  1.5481e+11   Root MSE        =
2.2e+05

------------------------------------------------------------------------------
-
art_Terro~47 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |   41420.51   10710.65     3.87   0.001     19480.73
63360.29
intervention |  -693616.9   154640.9    -4.49   0.000     -1010384   -
376849.4
   postslope |   -67513.1   16789.25    -4.02   0.000    -101904.3   -
33121.89
       _cons |    2289153   109751.5    20.86   0.000      2064337
2513968
------------------------------------------------------------------------------
-
=========
art_Global2
===========

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
10.06
       Model |   6663270.2         3  2221090.07   Prob > F        =
0.0001
    Residual |   6180561.8        28   220734.35   R-squared       =
0.5188
```

```
-------------+----------------------------------   Adj R-squared   =
0.4672
       Total |    12843832        31  414317.161   Root MSE        =
469.82

-----------------------------------------------------------------------------
-
 art_Global2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
  monthindex |   114.3824   23.25974     4.92   0.000     66.73693
162.0278
intervention |  -1535.819   335.8252    -4.57   0.000    -2223.726   -
847.9123
   postslope |  -46.97164   36.46029    -1.29   0.208    -121.6572
27.71387
       _cons |     8313.5   238.3414    34.88   0.000      7825.28
8801.72
-----------------------------------------------------------------------------
-
=========
art_Terror_31
===========

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
20.87
       Model |  5.1404e+11         3  1.7135e+11   Prob > F        =
0.0000
    Residual |  2.2989e+11        28  8.2102e+09   R-squared       =
0.6910
-------------+----------------------------------   Adj R-squared   =
0.6579
       Total |  7.4392e+11        31  2.3998e+10   Root MSE        =
90610

-----------------------------------------------------------------------------
-
art_Terro~31 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
  monthindex |   28484.13   4485.873     6.35   0.000     19295.24
37673.02
intervention |  -253556.5   64767.24    -3.91   0.001    -386226.2   -
120886.9
```

```
   postslope |  -41554.21    7031.73    -5.91   0.000    -55958.05   -
27150.36
       _cons |   471146.3   45966.52    10.25   0.000     376988.2
565304.5
------------------------------------------------------------------------------
-
=========
art_Security
===========

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
0.91
       Model |  7.5795e+10         3  2.5265e+10   Prob > F        =
0.4470
    Residual |  7.7441e+11        28  2.7657e+10   R-squared       =
0.0891
-------------+----------------------------------   Adj R-squared   =   -
0.0084
       Total |  8.5020e+11        31  2.7426e+10   Root MSE        =
1.7e+05

------------------------------------------------------------------------------
-
art_Security |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |   11135.07   8233.343     1.35   0.187     -5730.17
28000.31
intervention |  -24638.34   118873.4    -0.21   0.837    -268139.4
218862.7
   postslope |  -20465.87   12905.99    -1.59   0.124     -46902.6
5970.859
       _cons |   708187.4   84366.66     8.39   0.000     535370.2
881004.7
------------------------------------------------------------------------------
-
=========
art_Popular
===========

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
0.34
       Model |  1.4789e+13         3  4.9297e+12   Prob > F        =
0.7938
```

```
    Residual |  4.0134e+14        28  1.4334e+13   R-squared       =
0.0355
-------------+----------------------------------   Adj R-squared   =   -
0.0678
       Total |  4.1613e+14        31  1.3424e+13   Root MSE        =
3.8e+06

------------------------------------------------------------------------------
-
 art_Popular |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |  -48458.14   187433.7    -0.26   0.798    -432398.7
335482.5
intervention |   -1716643    2706177    -0.63   0.531     -7259994
3826709
   postslope |   177324.7   293807.6     0.60   0.551    -424512.8
779162.2
       _cons |   2.58e+07    1920624    13.41   0.000     2.18e+07
2.97e+07
------------------------------------------------------------------------------
-
=========
art_Infrastructure
===========

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
27.12
       Model |  3.0280e+11         3  1.0093e+11   Prob > F        =
0.0000
    Residual |  1.0421e+11        28  3.7218e+09   R-squared       =
0.7440
-------------+----------------------------------   Adj R-squared   =
0.7165
       Total |  4.0701e+11        31  1.3129e+10   Root MSE        =
61007

------------------------------------------------------------------------------
-
art_Infras~e |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |  -11079.82   3020.285    -3.67   0.001    -17266.59   -
4893.042
```

```
intervention |  -12721.07   43607.01    -0.29   0.773      -102046
76603.85
   postslope |   2431.841   4734.381     0.51   0.612    -7266.098
12129.78
       _cons |   771772.3   30948.71    24.94   0.000     708376.8
835167.9
-----------------------------------------------------------------------------
-
=========
art_Global1
===========

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
20.64
       Model |  10062791.9         3  3354263.97   Prob > F        =
0.0000
    Residual |  4549258.31        28  162473.511   R-squared       =
0.6887
-------------+----------------------------------   Adj R-squared   =
0.6553
       Total |  14612050.2        31  471356.459   Root MSE        =
403.08

-----------------------------------------------------------------------------
-
 art_Global1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
  monthindex |   70.57598   19.95544     3.54   0.001     29.69912
111.4528
intervention |  -1397.969   288.1175    -4.85   0.000    -1988.151   -
807.7867
   postslope |  -90.97598    31.2807    -2.91   0.007    -155.0516   -
26.90038
       _cons |    7385.11   204.4824    36.12   0.000     6966.247
7803.973
-----------------------------------------------------------------------------
-

. * table 8 replication
. regress art_Terror_31 monthindex intervention postslope art_Global1

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(4, 27)        =
16.30
```

```
       Model |  5.2604e+11         4  1.3151e+11   Prob > F        =
0.0000
    Residual |  2.1789e+11        27  8.0700e+09   R-squared       =
0.7071
-------------+----------------------------------   Adj R-squared   =
0.6637
       Total |  7.4392e+11        31  2.3998e+10   Root MSE        =
89833

------------------------------------------------------------------------------
-
art_Terro~31 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |   32108.35   5349.312     6.00   0.000     21132.46
43084.23
intervention |    -325345   87120.19    -3.73   0.001    -504100.9   -
146589.1
   postslope |  -46226.01   7955.041    -5.81   0.000     -62548.4   -
29903.61
 art_Global1 |  -51.35198   42.11781    -1.22   0.233    -137.7706
35.06662
       _cons |   850386.4   314365.4     2.71   0.012     205361.8
1495411
------------------------------------------------------------------------------
-

. * table 9 replication
. regress art_Terror_47 monthindex intervention postslope art_Global1

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(4, 27)        =
18.49
       Model |  3.5157e+12         4  8.7893e+11   Prob > F        =
0.0000
    Residual |  1.2835e+12        27  4.7538e+10   R-squared       =
0.7326
-------------+----------------------------------   Adj R-squared   =
0.6929
       Total |  4.7992e+12        31  1.5481e+11   Root MSE        =
2.2e+05

------------------------------------------------------------------------------
-
art_Terro~47 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
```

```
-------------+----------------------------------------------------------------
-
  monthindex |   35983.25   12983.28     2.77   0.010     9343.768
62622.74
intervention |  -585915.8   211448.8    -2.77   0.010     -1019773   -
152058.7
   postslope |   -60504.2   19307.63    -3.13   0.004    -100120.2   -
20888.23
 art_Global1 |   77.04117   102.2238     0.75   0.458    -132.7048
286.7872
       _cons |    1720195   762994.1     2.25   0.032     154660.4
3285730
------------------------------------------------------------------------------
-

. * control regs
. regress art_Global2 monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
10.06
       Model |   6663270.2         3  2221090.07   Prob > F        =
0.0001
    Residual |   6180561.8        28   220734.35   R-squared       =
0.5188
-------------+----------------------------------   Adj R-squared   =
0.4672
       Total |    12843832        31  414317.161   Root MSE        =
469.82

------------------------------------------------------------------------------
-
 art_Global2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |   114.3824   23.25974     4.92   0.000     66.73693
162.0278
intervention |  -1535.819   335.8252    -4.57   0.000    -2223.726   -
847.9123
   postslope |  -46.97164   36.46029    -1.29   0.208    -121.6572
27.71387
       _cons |     8313.5   238.3414    34.88   0.000      7825.28
8801.72
------------------------------------------------------------------------------
-

.
```

```
. * show that may and april also stat signif
. gen interventionmay=intervention

. replace interventionmay=1 if monthindex==17
(1 real change made)

. gen postslopemay=postslope

. replace postslopemay=postslope+1 if interventionmay==1
(16 real changes made)

. gen interventionapril=interventionmay

. replace interventionapril=1 if monthindex==16
(1 real change made)

. gen postslopeapril=postslopemay

. replace postslopeapril=postslopeapril + 1 if interventionapril==1
(17 real changes made)

. list monthindex postslope postslopeapril postslopemay intervention
interventionapril interventionmay

     +-----------------------------------------------------------------------
-----+
     | monthi~x   postsl~e   postsl~l   postsl~y   interv~n   interv~l
interv~y |
     |-----------------------------------------------------------------------
-----|
  1. |        1          0          0          0          0          0
0 |
  2. |        2          0          0          0          0          0
0 |
  3. |        3          0          0          0          0          0
0 |
  4. |        4          0          0          0          0          0
0 |
  5. |        5          0          0          0          0          0
0 |
     |-----------------------------------------------------------------------
-----|
  6. |        6          0          0          0          0          0
0 |
  7. |        7          0          0          0          0          0
0 |
  8. |        8          0          0          0          0          0
0 |
  9. |       9         0         0         0         0         0
0 |
 10. |      10         0         0         0         0         0
0 |
     |-----------------------------------------------------------------
-----|
 11. |      11         0         0         0         0         0
0 |
 12. |      12         0         0         0         0         0
0 |
 13. |      13         0         0         0         0         0
0 |
 14. |      14         0         0         0         0         0
0 |
 15. |      15         0         0         0         0         0
0 |
     |-----------------------------------------------------------------
-----|
 16. |      16         0         1         0         0         1
0 |
 17. |      17         0         2         1         0         1
1 |
 18. |      18         1         3         2         1         1
1 |
 19. |      19         2         4         3         1         1
1 |
 20. |      20         3         5         4         1         1
1 |
     |-----------------------------------------------------------------
-----|
 21. |      21         4         6         5         1         1
1 |
 22. |      22         5         7         6         1         1
1 |
 23. |      23         6         8         7         1         1
1 |
 24. |      24         7         9         8         1         1
1 |
 25. |      25         8        10         9         1         1
1 |
     |-----------------------------------------------------------------
-----|
 26. |      26         9        11        10         1         1
1 |
 27. |      27        10        12        11         1         1
1 |
 28. |      28        11        13        12         1         1
1 |
 29. |       29          12          14          13           1          1
1 |
 30. |       30          13          15          14           1          1
1 |
     |------------------------------------------------------------------------
-----|
 31. |       31          14          16          15           1          1
1 |
 32. |       32          15          17          16           1          1
1 |
     +------------------------------------------------------------------------
-----+

. *
. * estimate turning point (estimated peak of data)
. gen idx2=monthindex^2

. regress art_Terror_48 monthindex idx2

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(2, 29)        =
2.60
       Model |  9.6611e+11         2  4.8306e+11   Prob > F        =
0.0917
    Residual |  5.3928e+12        29  1.8596e+11   R-squared       =
0.1519
-------------+----------------------------------   Adj R-squared   =
0.0934
       Total |  6.3590e+12        31  2.0513e+11   Root MSE        =
4.3e+05

------------------------------------------------------------------------------
-
art_Terro~48 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |   20575.12   34056.48     0.60   0.550     -49078.2
90228.43
        idx2 |  -1120.311   1001.228    -1.12   0.272    -3168.052
927.4307
       _cons |    2589880   243771.8    10.62   0.000      2091311
3088449
------------------------------------------------------------------------------
-

. predict tmp48
(option xb assumed; fitted values)
```

```
. egen max48=max(tmp48)

. list viewsdate monthindex if tmp48==max48

     +-----------------------+
     |  viewsdate   monthi~x |
     |-----------------------|
  9. | 09/01/2012          9 |
     +-----------------------+

.
. regress art_Terror_47 monthindex idx2

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(2, 29)        =
12.52
       Model |  2.2234e+12         2  1.1117e+12   Prob > F        =
0.0001
    Residual |  2.5758e+12        29  8.8822e+10   R-squared       =
0.4633
-------------+----------------------------------   Adj R-squared   =
0.4263
       Total |  4.7992e+12        31  1.5481e+11   Root MSE        =
3.0e+05

-----------------------------------------------------------------------------
-
art_Terro~47 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
  monthindex |   43574.63      23537     1.85   0.074     -4563.94
91713.19
        idx2 |  -2022.568   691.9654    -2.92   0.007    -3437.796   -
607.3393
       _cons |    2398370   168474.8    14.24   0.000      2053801
2742940
-----------------------------------------------------------------------------
-

. predict tmp47
(option xb assumed; fitted values)

. egen max47=max(tmp47)

. list viewsdate monthindex if tmp47==max47
```

```
     +------------------------+
     |  viewsdate   monthi~x |
     |------------------------|
 11. | 11/01/2012         11 |
     +------------------------+

.
. regress art_Terror_31 monthindex idx2

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(2, 29)        =
9.35
       Model |  2.9173e+11         2  1.4586e+11   Prob > F        =
0.0007
    Residual |  4.5220e+11        29  1.5593e+10   R-squared       =
0.3921
-------------+----------------------------------   Adj R-squared   =
0.3502
       Total |  7.4392e+11        31  2.3998e+10   Root MSE        =
1.2e+05

------------------------------------------------------------------------------
-
art_Terro~31 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |   36223.88   9861.789     3.67   0.001     16054.26
56393.51
        idx2 |  -1193.715   289.9272    -4.12   0.000    -1786.683   -
600.7469
       _cons |   495510.5    70589.4     7.02   0.000       351139
639882
------------------------------------------------------------------------------
-

. predict tmp31
(option xb assumed; fitted values)

. egen max31=max(tmp31)

. list viewsdate monthindex if tmp31==max31

     +------------------------+
     |  viewsdate   monthi~x |
     |------------------------|
 15. | 03/01/2013         15 |
     +------------------------+
.
. drop tmp31 tmp47 tmp48 max31 max47 max48

.
. *
. regress art_Terror_31 monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
20.87
       Model |  5.1404e+11         3  1.7135e+11   Prob > F        =
0.0000
    Residual |  2.2989e+11        28  8.2102e+09   R-squared       =
0.6910
-------------+----------------------------------   Adj R-squared   =
0.6579
       Total |  7.4392e+11        31  2.3998e+10   Root MSE        =
90610

-----------------------------------------------------------------------------
-
art_Terro~31 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
  monthindex |   28484.13   4485.873     6.35   0.000     19295.24
37673.02
intervention |  -253556.5   64767.24    -3.91   0.001    -386226.2   -
120886.9
   postslope |  -41554.21    7031.73    -5.91   0.000    -55958.05   -
27150.36
       _cons |   471146.3   45966.52    10.25   0.000     376988.2
565304.5
-----------------------------------------------------------------------------
-

. regress art_Terror_31 monthindex interventionmay postslopemay

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
14.66
       Model |  4.5452e+11         3  1.5151e+11   Prob > F        =
0.0000
    Residual |  2.8941e+11        28  1.0336e+10   R-squared       =
0.6110
```

```
-------------+----------------------------------   Adj R-squared   =
0.5693
       Total |  7.4392e+11        31  2.3998e+10   Root MSE        =
1.0e+05

------------------------------------------------------------------------------
----
  art_Terror_31 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
----------------+-------------------------------------------------------------
----
     monthindex |   27831.07   5513.605     5.05   0.000     16536.96
39125.18
interventionmay |    -135552   72099.74    -1.88   0.071    -283241.6
12137.67
   postslopemay |  -47070.54   7797.415    -6.04   0.000    -63042.82   -
31098.26
          _cons |   475064.7   53314.02     8.91   0.000     365855.8
584273.5
------------------------------------------------------------------------------
----

. regress art_Terror_31 monthindex interventionapril postslopeapril

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
12.16
       Model |  4.2092e+11         3  1.4031e+11   Prob > F        =
0.0000
    Residual |  3.2300e+11        28  1.1536e+10   R-squared       =
0.5658
-------------+----------------------------------   Adj R-squared   =
0.5193
       Total |  7.4392e+11        31  2.3998e+10   Root MSE        =
1.1e+05

------------------------------------------------------------------------------
------
    art_Terror_31 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
------------------+-----------------------------------------------------------
------
       monthindex |   19718.72   6418.652     3.07   0.005     6570.704
32866.73
interventionapril |   85936.01   75872.03     1.13   0.267    -69480.79
241352.8
   postslopeapril |  -47183.37   8335.046    -5.66   0.000    -64256.94    -
30109.8
```

```
            _cons |   521034.7   58359.17     8.93   0.000     401491.3
640578
------------------------------------------------------------------------------
------

.
. regress art_Terror_47 monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
24.85
       Model |  3.4887e+12         3  1.1629e+12   Prob > F        =
0.0000
    Residual |  1.3105e+12        28  4.6805e+10   R-squared       =
0.7269
-------------+----------------------------------   Adj R-squared   =
0.6977
       Total |  4.7992e+12        31  1.5481e+11   Root MSE        =
2.2e+05

------------------------------------------------------------------------------
-
art_Terro~47 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |   41420.51   10710.65     3.87   0.001     19480.73
63360.29
intervention |  -693616.9   154640.9    -4.49   0.000     -1010384   -
376849.4
   postslope |   -67513.1   16789.25    -4.02   0.000    -101904.3   -
33121.89
       _cons |    2289153   109751.5    20.86   0.000      2064337
2513968
------------------------------------------------------------------------------
-

. regress art_Terror_47 monthindex interventionmay postslopemay

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
19.19
       Model |  3.2291e+12         3  1.0764e+12   Prob > F        =
0.0000
    Residual |  1.5701e+12        28  5.6077e+10   R-squared       =
0.6728
```

```
-------------+----------------------------------   Adj R-squared   =
0.6378
       Total |  4.7992e+12        31  1.5481e+11   Root MSE        =
2.4e+05

------------------------------------------------------------------------------
----
  art_Terror_47 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
----------------+-------------------------------------------------------------
----
     monthindex |   43914.21   12842.55     3.42   0.002     17607.45
70220.98
interventionmay |  -502573.7   167938.1    -2.99   0.006    -846579.3   -
158568.1
   postslopemay |  -83106.85   18162.11    -4.58   0.000    -120310.2   -
45903.46
          _cons |    2274190   124181.5    18.31   0.000      2019816
2528565
------------------------------------------------------------------------------
----

. regress art_Terror_47 monthindex interventionapril postslopeapril

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
14.09
       Model |  2.8871e+12         3  9.6236e+11   Prob > F        =
0.0000
    Residual |  1.9122e+12        28  6.8291e+10   R-squared       =
0.6016
-------------+----------------------------------   Adj R-squared   =
0.5589
       Total |  4.7992e+12        31  1.5481e+11   Root MSE        =
2.6e+05

------------------------------------------------------------------------------
------
    art_Terror_47 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
------------------+-----------------------------------------------------------
------
       monthindex |   37869.78   15617.23     2.42   0.022     5879.338
69860.22
interventionapril |  -195021.8   184604.3    -1.06   0.300    -573166.5
183122.9
   postslopeapril |  -91064.94   20280.01    -4.49   0.000    -132606.7   -
49523.23
```

```
            _cons |    2308442   141993.7    16.26   0.000      2017581
2599303
-----------------------------------------------------------------------------
------

.
. regress art_Terror_47 monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
24.85
       Model |  3.4887e+12         3  1.1629e+12   Prob > F        =
0.0000
    Residual |  1.3105e+12        28  4.6805e+10   R-squared       =
0.7269
-------------+----------------------------------   Adj R-squared   =
0.6977
       Total |  4.7992e+12        31  1.5481e+11   Root MSE        =
2.2e+05

-----------------------------------------------------------------------------
-
art_Terro~47 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
  monthindex |   41420.51   10710.65     3.87   0.001     19480.73
63360.29
intervention |  -693616.9   154640.9    -4.49   0.000     -1010384   -
376849.4
   postslope |   -67513.1   16789.25    -4.02   0.000    -101904.3   -
33121.89
       _cons |    2289153   109751.5    20.86   0.000      2064337
2513968
-----------------------------------------------------------------------------
-

. regress art_Terror_47 monthindex interventionmay postslopemay

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
19.19
       Model |  3.2291e+12         3  1.0764e+12   Prob > F        =
0.0000
    Residual |  1.5701e+12        28  5.6077e+10   R-squared       =
0.6728
```

```
-------------+----------------------------------   Adj R-squared   =
0.6378
       Total |  4.7992e+12        31  1.5481e+11   Root MSE        =
2.4e+05

-----------------------------------------------------------------------------
----
  art_Terror_47 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
----------------+------------------------------------------------------------
----
     monthindex |   43914.21   12842.55     3.42   0.002     17607.45
70220.98
interventionmay |  -502573.7   167938.1    -2.99   0.006    -846579.3   -
158568.1
   postslopemay |  -83106.85   18162.11    -4.58   0.000    -120310.2   -
45903.46
          _cons |    2274190   124181.5    18.31   0.000      2019816
2528565
-----------------------------------------------------------------------------
----

. regress art_Terror_47 monthindex interventionapril postslopeapril

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
14.09
       Model |  2.8871e+12         3  9.6236e+11   Prob > F        =
0.0000
    Residual |  1.9122e+12        28  6.8291e+10   R-squared       =
0.6016
-------------+----------------------------------   Adj R-squared   =
0.5589
       Total |  4.7992e+12        31  1.5481e+11   Root MSE        =
2.6e+05

-----------------------------------------------------------------------------
------
    art_Terror_47 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
------------------+----------------------------------------------------------
------
       monthindex |   37869.78   15617.23     2.42   0.022     5879.338
69860.22
interventionapril |  -195021.8   184604.3    -1.06   0.300    -573166.5
183122.9
   postslopeapril |  -91064.94   20280.01    -4.49   0.000    -132606.7   -
49523.23
```

```
            _cons |    2308442   141993.7    16.26   0.000      2017581
2599303
------------------------------------------------------------------------------
------

.
. reshape long art_, i( monthindex date1 month1 year1 intervention postslope)
j(artnmshort) string
(note: j = Global1 Global2 Infrastructure Popular Security Terror_31
Terror_47 Terror_48)

Data                               wide   ->   long
------------------------------------------------------------------------------
Number of obs.                       32   ->     256
Number of variables                  20   ->      14
j variable (8 values)                     ->   artnmshort
xij variables:
art_Global1 art_Global2 ... art_Terror_48 ->   art_
------------------------------------------------------------------------------

. rename art_ pageviews

. format pageviews %12.0f

. egen rankviews=rank(pageviews), by(artnmshort)

.  gen yearmonth1=year*100+month1

. * most groups peaked in earlier period (not unique to terror articles) and
no group peaked in May 2013 (just before claim
> ed intervention)
. list year1 month1 artnmshort if rankviews==32

     +---------------------------------+
     | year1   month1       artnmshort |
     |---------------------------------|
  3. |  2012        1   Infrastructure |
 52. |  2012        7          Popular |
 88. |  2012       11        Terror_48 |
 97. |  2013        1          Global1 |
 98. |  2013        1          Global2 |
     |---------------------------------|
126. |  2013        4        Terror_31 |
127. |  2013        4        Terror_47 |
181. |  2013       11         Security |
     +---------------------------------+

. * trough
. list year1 month1 artnmshort if rankviews==1
```

```
     +---------------------------------+
     | year1   month1      artnmshort |
     |---------------------------------|
161. |  2013        9         Global1 |
162. |  2013        9         Global2 |
172. |  2013       10         Popular |
198. |  2014        1       Terror_31 |
199. |  2014        1       Terror_47 |
     |---------------------------------|
200. |  2014        1       Terror_48 |
251. |  2014        8  Infrastructure |
253. |  2014        8        Security |
     +---------------------------------+

.
. *
. * write out to csv file in order to produce graphs
. outsheet using articlesaggregate.csv, comma replace

.
. *****************************
. * replicate control regressions
. *****************************
. clear

. use security25

. regress sum_view monthindex postslope intervention

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
0.91
       Model |  7.5795e+10         3  2.5265e+10   Prob > F        =
0.4470
    Residual |  7.7441e+11        28  2.7657e+10   R-squared       =
0.0891
-------------+----------------------------------   Adj R-squared   =   -
0.0084
       Total |  8.5020e+11        31  2.7426e+10   Root MSE        =
1.7e+05

-----------------------------------------------------------------------------
-
    sum_view |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
```

```
  monthindex |   11135.07   8233.343     1.35   0.187     -5730.17
28000.31
   postslope |  -20465.87   12905.99    -1.59   0.124     -46902.6
5970.859
intervention |  -24638.34   118873.4    -0.21   0.837    -268139.4
218862.7
       _cons |   708187.4   84366.66     8.39   0.000     535370.2
881004.7
-----------------------------------------------------------------------------
-

. outsheet using security25.csv, comma replace

.
. use  infrastructure34

. regress sum_view monthindex postslope intervention

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
27.12
       Model |  3.0280e+11         3  1.0093e+11   Prob > F        =
0.0000
    Residual |  1.0421e+11        28  3.7218e+09   R-squared       =
0.7440
-------------+----------------------------------   Adj R-squared   =
0.7165
       Total |  4.0701e+11        31  1.3129e+10   Root MSE        =
61007

-----------------------------------------------------------------------------
-
    sum_view |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
  monthindex |  -11079.82   3020.285    -3.67   0.001    -17266.59   -
4893.042
   postslope |   2431.841   4734.381     0.51   0.612    -7266.098
12129.78
intervention |  -12721.07   43607.01    -0.29   0.773      -102046
76603.85
       _cons |   771772.3   30948.71    24.94   0.000     708376.8
835167.9
-----------------------------------------------------------------------------
-

. outsheet using infrastructure34.csv, comma replace
```

```
.
. use popular26

. regress sum_view monthindex postslope intervention

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
0.34
       Model |  1.4789e+13         3  4.9297e+12   Prob > F        =
0.7938
    Residual |  4.0134e+14        28  1.4334e+13   R-squared       =
0.0355
-------------+----------------------------------   Adj R-squared   =   -
0.0678
       Total |  4.1613e+14        31  1.3424e+13   Root MSE        =
3.8e+06

------------------------------------------------------------------------------
-
    sum_view |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |  -48458.14   187433.7    -0.26   0.798    -432398.7
335482.5
   postslope |   177324.7   293807.6     0.60   0.551    -424512.8
779162.2
intervention |   -1716643    2706177    -0.63   0.531     -7259994
3826709
       _cons |   2.58e+07    1920624    13.41   0.000     2.18e+07
2.97e+07
------------------------------------------------------------------------------
-

. outsheet using popular26.csv, comma replace

.
. clear

.
. ******************************
. * now use with individual 48
. ******************************
. clear

. use artterror48_origplusrecentdates.dta
. gen date1=date(dateorig,"MDY")

. gen month1=month(date1)

. gen year1=year(date1)

. sort date1

. gen monthindex=_n

. * account for skipped 11 months
. replace monthindex = monthindex + 10 if year>=2015
(41 real changes made)

. gen intervention=1

. replace intervention=0 if date1<date("06/01/2013","MDY")
(17 real changes made)

. gen postslope = (monthindex-17)*intervention

. egen totview=rowtotal(art_t*)

.
. * check first regression again
. regress totview monthindex postslope intervention if year<=2014

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
9.16
       Model |  3.1498e+12         3  1.0499e+12   Prob > F        =
0.0002
    Residual |  3.2091e+12        28  1.1461e+11   R-squared       =
0.4953
-------------+----------------------------------   Adj R-squared   =
0.4413
       Total |  6.3590e+12        31  2.0513e+11   Root MSE        =
3.4e+05

-----------------------------------------------------------------------------
-
     totview |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
  monthindex |   47038.28   16760.41     2.81   0.009     12706.13
81370.43
```

```
   postslope |  -35517.69   26272.41    -1.35   0.187    -89334.29
18298.91
intervention |  -995085.2   241987.6    -4.11   0.000     -1490774   -
499396.1
       _cons |    2352364   171743.1    13.70   0.000      2000564
2704164
------------------------------------------------------------------------------
-

. gen totviewminushamas=totview - art_t22

. gen totviewminusdup=totview - art_t47

. regress totviewminushamas monthindex postslope intervention if year1<=2014

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
24.85
       Model |  3.4887e+12         3  1.1629e+12   Prob > F        =
0.0000
    Residual |  1.3105e+12        28  4.6805e+10   R-squared       =
0.7269
-------------+----------------------------------   Adj R-squared   =
0.6977
       Total |  4.7992e+12        31  1.5481e+11   Root MSE        =
2.2e+05

------------------------------------------------------------------------------
-
totviewmin~s |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
  monthindex |   41420.51   10710.65     3.87   0.001     19480.73
63360.29
   postslope |   -67513.1   16789.25    -4.02   0.000    -101904.3   -
33121.89
intervention |  -693616.9   154640.9    -4.49   0.000     -1010384   -
376849.4
       _cons |    2289153   109751.5    20.86   0.000      2064337
2513968
------------------------------------------------------------------------------
-

. *
. regress totviewminusdup monthindex postslope intervention if year1<=2014
```

```
      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
8.83
       Model |  2.9756e+12         3  9.9188e+11   Prob > F        =
0.0003
    Residual |  3.1438e+12        28  1.1228e+11   R-squared       =
0.4863
-------------+----------------------------------   Adj R-squared   =
0.4312
       Total |  6.1195e+12        31  1.9740e+11   Root MSE        =
3.4e+05

-----------------------------------------------------------------------------
-
totviewmin~p |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
  monthindex |   43262.98   16589.01     2.61   0.014     9281.937
77244.02
   postslope |  -28278.84   26003.73    -1.09   0.286    -81545.06
24987.39
intervention |  -985297.4   239512.8    -4.11   0.000     -1475917   -
494677.6
       _cons |    2325107   169986.8    13.68   0.000      1976905
2673309
-----------------------------------------------------------------------------
-


.
. *
. * now drop totals and reshape
. drop totv*

. * obvious error in articles on Recruitment and fundamentalism (all numbers
but last couple are the same)
. count if art_t46==art_t47
  30


.
. reshape long art_t, i( monthindex date1 month1 year1 intervention
postslope) j(artnum)
(note: j = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 4
> 1 42 43 44 45 46 47 48)

Data                               wide   ->   long
-----------------------------------------------------------------------------
```

```
Number of obs.                       73   ->    3504
Number of variables                  55   ->       9
j variable (48 values)                    ->   artnum
xij variables:
              art_t1 art_t2 ... art_t48   ->   art_t
-----------------------------------------------------------------------------

. *
. rename art_t pageviews

.
. * pull in article names
. sort artnum

. merge m:1 artnum using articlenames48
(note: variable artnum was byte, now float to accommodate using data's
values)

    Result                           # of obs.
    -----------------------------------------
    not matched                             0
    matched                             3,504  (_merge==3)
    -----------------------------------------

. assert _merge==3

. drop _merge

. * normalize names for better display and read/write
. replace artnames=subinstr(artnames,"(","_",.)
(146 real changes made)

. replace artnames=subinstr(artnames,")","_",.)
(73 real changes made)

. replace artnames=subinstr(artnames," ","_",.)
(1,679 real changes made)

. replace artnames=subinstr(artnames,"+","_",.)
(73 real changes made)

. replace artnames=subinstr(artnames,"-","_",.)
(146 real changes made)

. replace artnames=subinstr(artnames,"__","_",.)
(73 real changes made)

. replace artnames=subinstr(artnames,"__","_",.)
(73 real changes made)
```

```
. replace artnames=subinstr(artnames,"__","_",.)
(0 real changes made)

.
. * pull in indicator of whether article was high privacy
. sort artnum

. merge m:1 artnum using highprivacy31

    Result                           # of obs.
    -----------------------------------------
    not matched                         1,241
        from master                     1,241  (_merge==1)
        from using                          0  (_merge==2)

    matched                             2,263  (_merge==3)
    -----------------------------------------

. gen highprivind=_merge==3

. assert _merge!=2

. drop _merge

. *
. * indicate 7 articles with issues between early and late period
. gen lateissueind=0

. replace lateissueind=1 if artname=="terror"
(73 real changes made)

. replace lateissueind=1 if artname=="Weapons_grade"
(73 real changes made)

. replace lateissueind=1 if artname=="_Euskadi_ta_Askatasuna"
(73 real changes made)

. replace lateissueind=1 if artname=="Pirates"
(73 real changes made)

. replace lateissueind=1 if artname=="Islamist"
(73 real changes made)

. replace lateissueind=1 if artname=="Recruitment"
(73 real changes made)

. replace lateissueind=1 if artname=="Fundamentalism"
(73 real changes made)
```

```
.
.
.
. * check that high privacy desig is ok by checking reg of sum
. egen totview31=sum(pageviews), by(monthindex highprivind)

. replace totview31=. if highprivind==0
(1,241 real changes made, 1,241 to missing)

. bysort monthindex highprivind: gen tmpindx=_n

. regress totview31 monthindex postslope intervention if tmpindx==1 &
year1<=2014

      Source |       SS           df       MS      Number of obs   =
32
-------------+----------------------------------   F(3, 28)        =
20.87
       Model |  5.1404e+11         3  1.7135e+11   Prob > F        =
0.0000
    Residual |  2.2989e+11        28  8.2102e+09   R-squared       =
0.6910
-------------+----------------------------------   Adj R-squared   =
0.6579
       Total |  7.4392e+11        31  2.3998e+10   Root MSE        =
90610

-----------------------------------------------------------------------------
-
   totview31 |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+---------------------------------------------------------------
-
  monthindex |   28484.13   4485.873     6.35   0.000     19295.24
37673.02
   postslope |  -41554.21    7031.73    -5.91   0.000    -55958.05   -
27150.36
intervention |  -253556.5   64767.24    -3.91   0.001    -386226.2   -
120886.9
       _cons |   471146.3   45966.52    10.25   0.000     376988.2
565304.5
-----------------------------------------------------------------------------
-

. drop tmpindx

. *
. * get ranks of first 17, first 32 and all
. gen pageviewall=pageviews
(26 missing values generated)

. gen pageviews17=pageviews
(26 missing values generated)

. replace pageviews=. if year>2014
(1,942 real changes made, 1,942 to missing)

. replace pageviews17=. if monthindex>=18
(2,662 real changes made, 2,662 to missing)

. egen rankviewsearly=rank(pageviews), by(artnum)
(1968 missing values generated)

. egen maxrankearly=max(rankviewsearly), by(artnum)

. egen rankviews17=rank(pageviews17), by(artnum)
(2688 missing values generated)

. egen maxrank17=max(rankviews17), by(artnum)

. egen rankviewsall=rank(pageviewall), by(artnum)
(26 missing values generated)

. egen maxrankall=max(rankviewsall), by(artnum)

.
. sum maxr*

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
maxrankearly |      3,504          32           0         32         32
   maxrank17 |      3,504          17           0         17         17
  maxrankall |      3,504    72.45833    3.304247         50         73

. sum rankv*

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
rankviewse~y |      1,536        16.5    9.235782          1         32
 rankviews17 |        816           9    4.901734          1         17
rankviewsall |      3,478    36.80449    21.02188          1         73

. sort artnum date1

.
. *
. gen yearmonth=year1*100 + month1
. * summermonths lower in general --inidcation of seasonality
. * use rank so all data can be considered on a like to like basis
.  table month1, c(mean rankviewsearly median rankviewsearly mean
rankviewsall median rankviewsall n rankviewsall) row form
> at(%6.2f)

------------------------------------------------------------------------------
---
   month1 | mean(rank~y)  med(rankv~y)  mean(rank~l)  med(rankv~l)
N(rankvie~l)
----------+-------------------------------------------------------------------
---
        1 |        17.38         17.50         39.98         42.00
286
        2 |        16.72         17.00         35.92         36.00
286
        3 |        19.43         20.00         43.27         46.50
286
        4 |        17.34         17.00         39.69         39.50
286
        5 |        19.58         21.00         42.18         45.00
286
        6 |        14.20         14.00         32.54         31.00
287
        7 |        12.55         11.00         29.64         27.00
333
        8 |        11.77          9.00         28.67         27.00
333
        9 |        17.11         17.50         34.46         33.00
285
       10 |        20.39         22.00         40.94         42.00
286
       11 |        18.85         20.00         40.54         41.50
286
       12 |        14.18         14.00         36.27         39.00
238
          |
    Total |        16.50         16.50         36.80         37.00
3,478
------------------------------------------------------------------------------
---

.  table month1, c(mean rankviewsearly median rankviewsearly mean
rankviewsall median rankviewsall n rankviewsall) row form
> at(%6.2f)

------------------------------------------------------------------------------
---
```

```
   month1 | mean(rank~y)  med(rankv~y)  mean(rank~l)  med(rankv~l)
N(rankvie~l)
----------+-------------------------------------------------------------------
---
        1 |        17.38         17.50         39.98         42.00
286
        2 |        16.72         17.00         35.92         36.00
286
        3 |        19.43         20.00         43.27         46.50
286
        4 |        17.34         17.00         39.69         39.50
286
        5 |        19.58         21.00         42.18         45.00
286
        6 |        14.20         14.00         32.54         31.00
287
        7 |        12.55         11.00         29.64         27.00
333
        8 |        11.77          9.00         28.67         27.00
333
        9 |        17.11         17.50         34.46         33.00
285
       10 |        20.39         22.00         40.94         42.00
286
       11 |        18.85         20.00         40.54         41.50
286
       12 |        14.18         14.00         36.27         39.00
238
          |
    Total |        16.50         16.50         36.80         37.00
3,478
------------------------------------------------------------------------------
---

. regress rankviewsall i.month1 if lateissueind==0

      Source |       SS           df       MS      Number of obs   =
2,993
-------------+----------------------------------   F(11, 2981)     =
16.57
       Model |  76589.9048        11  6962.71861   Prob > F        =
0.0000
    Residual |   1252281.6     2,981  420.087754   R-squared       =
0.0576
-------------+----------------------------------   Adj R-squared   =
0.0542
       Total |   1328871.5     2,992  444.141544   Root MSE        =
20.496
```

```
-------------------------------------------------------------------------------
-
rankviewsall |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+-----------------------------------------------------------------
-
      month1 |
          2  |  -4.176829   1.848066    -2.26   0.024    -7.800443   -
.5532154
          3  |    3.03252   1.848066     1.64   0.101    -.5910936
6.656134
          4  |  -.5020325   1.848066    -0.27   0.786    -4.125646
3.121581
          5  |   2.004065   1.848066     1.08   0.278    -1.619549
5.627679
          6  |  -7.971545   1.848066    -4.31   0.000    -11.59516   -
4.347931
          7  |  -11.40418   1.780841    -6.40   0.000    -14.89598   -
7.912379
          8  |  -11.82578   1.780841    -6.64   0.000    -15.31759   -
8.333982
          9  |  -6.107724   1.848066    -3.30   0.001    -9.731337    -
2.48411
         10  |    .851626   1.848066     0.46   0.645    -2.771988
4.47524
         11  |   .6300813   1.848066     0.34   0.733    -2.993533
4.253695
         12  |  -3.890244   1.938268    -2.01   0.045    -7.690722   -
.0897656
             |
       _cons |       40.5    1.30678    30.99   0.000     37.93772
43.06228
-------------------------------------------------------------------------------
-

. regress rankviewsall i.month1 if monthindex<=32

      Source |       SS           df       MS      Number of obs   =
1,536
-------------+----------------------------------   F(11, 1524)     =
7.50
       Model |    40176.52        11  3652.41091   Prob > F        =
0.0000
    Residual |  741743.313     1,524  486.708211   R-squared       =
0.0514
-------------+----------------------------------   Adj R-squared   =
0.0445
       Total |  781919.833     1,535  509.394028   Root MSE        =
22.061
```

```
------------------------------------------------------------------------------
-
rankviewsall |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
-
      month1 |
          2  |  -.8854167   2.599969    -0.34   0.733    -5.985312
4.214478
          3  |   3.173611   2.599969     1.22   0.222    -1.926284
8.273506
          4  |  -.4930556   2.599969    -0.19   0.850     -5.59295
4.606839
          5  |   3.975694   2.599969     1.53   0.126      -1.1242
9.075589
          6  |  -6.152778   2.599969    -2.37   0.018    -11.25267   -
1.052883
          7  |  -9.854167   2.599969    -3.79   0.000    -14.95406   -
4.754272
          8  |  -10.05208   2.599969    -3.87   0.000    -15.15198   -
4.952188
          9  |   -.984375   2.906853    -0.34   0.735    -6.686231
4.717481
         10  |   5.869792   2.906853     2.02   0.044     .1679358
11.57165
         11  |   3.151042   2.906853     1.08   0.279    -2.550814
8.852898
         12  |  -5.104167   2.906853    -1.76   0.079    -10.80602
.5976892
             |
       _cons |   36.38542   1.838455    19.79   0.000     32.77925
39.99159
------------------------------------------------------------------------------
-

.
.  * where is maximum?
.  tab yearmonth highpriv  if rankviewsearly==maxrankearly

           |      highprivind
 yearmonth |         0          1 |     Total
-----------+----------------------+----------
    201201 |         2          0 |         2
    201202 |         0          2 |         2
    201203 |         0          1 |         1
    201205 |         1          1 |         2
    201206 |         1          0 |         1
    201208 |         1          0 |         1
    201209 |         0          1 |         1 
    201210 |         1          3 |         4 
    201211 |         2          1 |         3 
    201301 |         0          4 |         4 
    201302 |         1          0 |         1 
    201303 |         2          3 |         5 
    201304 |         0          8 |         8 
    201305 |         1          1 |         2 
    201307 |         1          0 |         1 
    201308 |         0          1 |         1 
    201309 |         0          1 |         1 
    201310 |         1          0 |         1 
    201311 |         0          1 |         1 
    201403 |         0          1 |         1 
    201405 |         1          1 |         2 
    201406 |         1          0 |         1 
    201407 |         1          1 |         2 
-----------+----------------------+----------
     Total |        17         31 |        48 


.  tab yearmonth highpriv  if rankviewsall==maxrankall

           |      highprivind
 yearmonth |         0          1 |     Total
-----------+----------------------+----------
    201202 |         0          1 |         1 
    201203 |         0          1 |         1 
    201210 |         1          2 |         3 
    201211 |         2          0 |         2 
    201301 |         0          1 |         1 
    201303 |         2          1 |         3 
    201304 |         0          6 |         6 
    201307 |         1          0 |         1 
    201309 |         0          1 |         1 
    201310 |         1          0 |         1 
    201311 |         0          1 |         1 
    201406 |         1          0 |         1 
    201407 |         1          0 |         1 
    201507 |         1          0 |         1 
    201511 |         1          6 |         7 
    201512 |         0          1 |         1 
    201601 |         0          1 |         1 
    201603 |         0          2 |         2 
    201604 |         0          1 |         1 
    201610 |         0          2 |         2 
    201703 |         1          0 |         1 
    201704 |         0          3 |         3 
    201705 |         1          0 |         1 
    201707 |         1          0 |         1 
    201805 |         0          1 |         1 
    201806 |         1          0 |         1 
    201810 |         1          0 |         1 
    201811 |         1          0 |         1 
-----------+----------------------+----------
     Total |        17         31 |        48 


. 
. * output to csv for graphics and other analysis
. gen dateformat=date1

. format dateformat %d

. 
. outsheet using orig48long.csv, comma replace

. *
. log close
      name:  <unnamed>
       log:  
D:\clients_2018\DOJ_Wiki_NSA\programsdata\readandreplicate_20190115.log
  log type:  text
 closed on:  15 Jan 2019, 18:07:40
```

**The following is a R code, used to produce the graphs:**

```
# libraries need to be commented in once per session
#library(dplyr)
# library(plyr)
#individual article data
# start with empty dataset
rm(list = ls())
art48incl2018<-
read.csv("D:\\clients_2018\\DOJ_Wiki_NSA\\programsdata\\orig48long.csv",sep="
,",header=T)
# article data as used in regressions (aggregated by group)
artagg<-
read.csv("D:\\clients_2018\\DOJ_Wiki_NSA\\programsdata\\articlesaggregate.csv
",sep=",",header=T)
# comparison datasets
compinfra34<-
read.csv("D:\\clients_2018\\DOJ_Wiki_NSA\\programsdata\\infrastructure34.csv"
,sep=",",header=T)
compsec25<-
read.csv("D:\\clients_2018\\DOJ_Wiki_NSA\\programsdata\\security25.csv",sep="
,",header=T)
```

```
comppop26<-
read.csv("D:\\clients_2018\\DOJ_Wiki_NSA\\programsdata\\popular26.csv",sep=",
",header=T)

# get labels for dates
artagg$dateabbr<-paste0(substr(as.character(artagg$date1),3,5),"-
",substr(as.character(artagg$date1),8,9))
art48incl2018$dateabbr<-
paste0(substr(as.character(art48incl2018$dateformat),3,5),"-
",substr(as.character(art48incl2018$dateformat),8,9))
if
(sum(unique(art48incl2018$monthindex)==sort(unique(art48incl2018$monthindex))
)<73) stop("Dates out of Order")
labellong<-unique(art48incl2018$dateabbr)
labelshort<-labellong[1:32]
# end date label

# create data without NAs and without data that has issues between 2014 and
later data
artincl2018noNA<-art48incl2018[!is.na(art48incl2018$rankviewsall),]
# just time through 2014
art48<-art48incl2018[art48incl2018$monthindex<=32,]
art48$artnames<-as.character(art48$artnames)
#######################
# get summary stats
#######################
sum2018noissue<-
ddply(artincl2018noNA[artincl2018noNA$lateissueind==0,],.(monthindex,interven
tion,postslope),summarise, mean1=mean(rankviewsall),
median1=median(rankviewsall),meanviews=mean(pageviewall),medviews=median(page
viewall))
sum2018_47noissue<-ddply(artincl2018noNA[artincl2018noNA$lateissueind==0 &
artincl2018noNA$artnames!="Hamas",],.(monthindex,intervention,postslope),summ
arise, mean1=mean(rankviewsall),
median1=median(rankviewsall),meanviews=mean(pageviewall),medviews=median(page
viewall))
sum2018_31noissue<-ddply(artincl2018noNA[artincl2018noNA$lateissueind==0 &
artincl2018noNA$highprivind==1,],.(monthindex,intervention,postslope),summari
se, mean1=mean(rankviewsall),
median1=median(rankviewsall),meanviews=mean(pageviewall),medviews=median(page
viewall))

sum2018all<-
ddply(artincl2018noNA,.(monthindex,intervention,postslope),summarise,
mean1=mean(rankviewsall),
median1=median(rankviewsall),meanviews=mean(pageviewall),medviews=median(page
viewall))
sum2014_48<-ddply(art48,.(monthindex,intervention,postslope),summarise,
mean1=mean(rankviewsall),
median1=median(rankviewsall),meanviews=mean(pageviewall),medviews=median(page
viewall))
sum2014_47<-
ddply(art48[art48$artnames!="Hamas",],.(monthindex,intervention,postslope),su
mmarise,mean1=mean(rankviewsall),
median1=median(rankviewsall),meanviews=mean(pageviewall),medviews=median(page
viewall))

sum2014_31<-
ddply(art48[art48$highprivind==1,],.(monthindex,intervention,postslope),summa
rise,mean1=mean(rankviewsall),median1=median(rankviewsall),meanviews=mean(pag
eviewall),medviews=median(pageviewall))


######################################
# show aggregate views and ranking by month
######################################
numagg<-length(unique(artagg$artnmshort))
artnms<-sort(unique(artagg$artnmshort),decreasing=T)
artnmslong<-as.character(artnms)
artnmslong[artnms=="Terror_48"]<-"Terror 48"
artnmslong[artnms=="Terror_47"]<-"Terror 48 without Hamas"
artnmslong[artnms=="Terror_31"]<-"High Privacy 31"

cols1<-
c("black","darkgreen","blue","green","magenta","orange","mediumorchid1","red"
)
lwd1<-c(rep(3,3),rep(1,5))
pch1<-c(7:9,0:2,5:6)
# aggregate  rank terror
tmpplot<-artagg[artagg$artnms==artnms[1],]
plot(tmpplot$monthindex,tmpplot$rankviews,type="b",pch=pch1[1],col=cols1[1],l
wd=lwd1[1],xlim=c(0,40),ylim=c(0,33),axes=F,ylab="Rank of Page Views by
Month: 1 is Lowest and 32 is Highest",xlab="")
for (i in 2:3) {
tmpplot<-artagg[artagg$artnms==artnms[i],]
lines(tmpplot$monthindex,tmpplot$rankviews,col=cols1[i],type="b",lwd=lwd1[i],
pch=pch1[i])
}
axis(1,1:32,label=unique(artagg$dateabbr),cex.axis=1,las=2)
axis(2,at=c(1,10,20,32))
legend("topright",legend=artnmslong[1:3],text.col=c(cols1[1:3]),cex=1.3)
abline(v=17.5,lwd=2)
# save with just terror articles
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/","aggregate_ran
k.png"),type="png")
# add controls
tmpplot<-artagg[artagg$artnms==artnms[1],]
```

```
plot(tmpplot$monthindex,tmpplot$rankviews,type="b",pch=pch1[1],col=cols1[1],l
wd=lwd1[1],xlim=c(0,40),ylim=c(1,32),axes=F,ylab="Rank of Page Views by
Month: 1 is Lowest and 32 is Highest",xlab="")
axis(1,1:32,label=unique(artagg$dateabbr),cex.axis=1,las=2)
axis(2,at=c(1,10,20,32))
for (i in 2:8) {
tmpplot<-artagg[artagg$artnms==artnms[i],]
lines(tmpplot$monthindex,tmpplot$rankviews,col=cols1[i],type="b",lwd=lwd1[i],
pch=pch1[i])
abline(v=17.5,lwd=2)

}
legend("topright",legend=artnmslong,text.col=cols1,pch=pch1,cex=1.2)
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/","aggregate_ran
kwithcontrols.png"),type="png")

## now plot each of the 8 separately

for (i in 4:8) {
tmpplot<-artagg[artagg$artnms==artnms[i],]
plot(tmpplot$monthindex,tmpplot$rankviews,type="b",pch=pch1[1],col=cols1[1],x
lim=c(0,32),ylim=c(0,33),axes=F,ylab="Rank of Page Views by Month: 1 is
Lowest and 32 is Highest",xlab="",lwd=2,main=paste("Rank of Views by Month
for Control:",artnms[i]))
axis(1,1:32,label=unique(artagg$dateabbr),cex.axis=1,las=2)
axis(2,at=c(1,10,20,32))
abline(v=17.5)
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/",
"aggregate_comp_", artnms[i],".png"),type="png")

}
###################################################
# now show total views (as in Figure 1 of Penney)
####################################################

tmpplot<-artagg[artagg$artnms==artnms[1],]
plot(tmpplot$monthindex,tmpplot$pageviews,type="b",pch=pch1[1],col=cols1[1],l
wd=lwd1[1],xlim=c(0,32),ylim=c(0,4200000),axes=F,ylab="Page Views in
Millions",xlab="")

for (i in 2:3) {
tmpplot<-artagg[artagg$artnms==artnms[i],]
lines(tmpplot$monthindex,tmpplot$pageviews,col=cols1[i],type="b",lwd=lwd1[i],
pch=pch1[i])
}
axis(1,1:32,label=unique(artagg$dateabbr),cex.axis=1,las=2)
axis(2,at=c(0,1,2,3,4,5)*1000000,label=paste((0:5),"MM"),las=2)
legend("topright",legend=artnmslong[1:3],text.col=c(cols1[1:3]))
abline(v=17.5,lwd=2)
```

```
# save with just terror articles
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/","aggregate32_s
um.png"),type="png")

######################################################################
# End aggregate graphs with controls
#######################################################################

####################################
# now look at terror data aggregates
#####################################
# look at mean and median views
# first median
plot(sum2018noissue$monthindex[1:32],sum2018noissue$medviews[1:32],type="b",a
xes=F,ylim=c(0,max(sum2018noissue$medviews*1.1)),xlab="",ylab="Median Number
of Page Views",lwd=2,xlim=c(0,75))

axis(1,at=c(1:32,35:75),label=labellong,las=2)
axis(2,at=c(0,10000,20000,30000,40000,50000),label=c("0","10K","20K","30K","4
0K","50K"))
abline(v=17.5)
title(main=" ")

lines(sum2018noissue$monthindex[1:32],sum2018_47noissue$medviews[1:32],col="r
ed",type="b",lty=2,lwd=2)
lines(sum2018noissue$monthindex[1:32],sum2018all$medviews[1:32],col="darkgree
n",type="b",lty=3,lwd=2)
lines(sum2018noissue$monthindex[1:32],sum2018_31noissue$medviews[1:32],col="b
lue",type="b",lty=4,lwd=2)

lines(sum2018noissue$monthindex[33:73]-
8,sum2018noissue$medviews[33:73],col="black",type="b",lty=2,lwd=2)
lines(sum2018noissue$monthindex[33:73]-
8,sum2018_47noissue$medviews[33:73],col="red",type="b",lty=2,lwd=2)
lines(sum2018noissue$monthindex[33:73]-
8,sum2018all$medviews[33:73],col="darkgreen",type="b",lty=3,lwd=2)
lines(sum2018noissue$monthindex[33:73]-
8,sum2018_31noissue$medviews[33:73],col="blue",type="b",lty=4,lwd=2)

abline(h=(1:9)*10000,lty=3)

legend(61,40000,legend=c("Terror 48","Terror 41","Terror 41 without
Hamas","High Privacy
26"),text.col=c("darkgreen","black","red","blue"),cex=1.2)

savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/","terror48plusm
edviews.png"),type="png")

# now mean views
```

```
plot(sum2018noissue$monthindex[1:32],sum2018noissue$meanviews[1:32],type="b",
axes=F,ylim=c(min(sum2018noissue$meanviews*.3),max(sum2018noissue$meanviews*1
.1)),xlab="",ylab="Average Number of Page Views",lwd=2,xlim=c(1,75))
axis(1,at=c(1:32,35:75),label=labellong,las=2)
axis(2,at=c(1:9)*10000,label=paste0(c(1:9)*10,"K"))
abline(v=17.5)
title(main=" ")


lines(sum2018noissue$monthindex[1:32],sum2018_47noissue$meanviews[1:32],col="
red",type="b",lty=2,lwd=2)
lines(sum2018noissue$monthindex[1:32],sum2018all$meanviews[1:32],col="darkgre
en",type="b",lty=3,lwd=2)
lines(sum2018noissue$monthindex[1:32],sum2018_31noissue$meanviews[1:32],col="
blue",type="b",lty=4,lwd=2)

lines(sum2018noissue$monthindex[33:73]-
8,sum2018noissue$meanviews[33:73],col="black",type="b",lty=2,lwd=2)
lines(sum2018noissue$monthindex[33:73]-
8,sum2018_47noissue$meanviews[33:73],col="red",type="b",lty=2,lwd=2)
lines(sum2018noissue$monthindex[33:73]-
8,sum2018all$meanviews[33:73],col="darkgreen",type="b",lty=3,lwd=2)
lines(sum2018noissue$monthindex[33:73]-
8,sum2018_31noissue$meanviews[33:73],col="blue",type="b",lty=4,lwd=2)
abline(h=(1:9)*10000,lty=3)

legend(60,105000,legend=c("Terror 48","Terror 41","Terror 41 without
Hamas","High Privacy
26"),text.col=c("darkgreen","black","red","blue"),cex=1.2)

savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/","terror48plusa
vgviews.png"),type="png")

##################################
# Just 32 months until aug 2014
##################################

plot(sum2014_48$monthindex,sum2014_48$meanviews,type="b",axes=F,ylim=c(min(su
m2014_48$meanviews*.3),max(sum2014_48$meanviews*1.1)),xlab="",ylab="Average
Number of Page Views",lwd=3,xlim=c(1,32),col="darkgreen")
axis(1,at=c(1:32),label=labelshort,las=2,cex.axis=1.5)
axis(2,at=c(1:9)*10000,label=paste0(c(1:9)*10,"K"))
abline(v=17.5)
#title(main=" ")


lines(sum2014_47$monthindex,sum2014_47$meanviews,col="red",type="b",lty=2,lwd
=3)
```

```
lines(sum2014_31$monthindex,sum2014_31$meanviews,col="blue",type="b",lty=4,lw
d=3)

abline(h=(1:9)*10000,lty=3)

legend("topright",legend=c("Terror 48","Terror 48 without Hamas","High
Privacy 31"),text.col=c("darkgreen","red","blue"),cex=1.5)
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/","terror48_2014
averageviews.png"),type="png")
#

plot(sum2014_48$monthindex,sum2014_48$medviews,type="b",axes=F,ylim=c(min(sum
2014_48$medviews*.3),max(sum2014_48$medviews*1.1)),xlab="",ylab="Median
Number of Page Views",lwd=3,xlim=c(1,32),col="darkgreen")
axis(1,at=c(1:32),label=labelshort,las=2,cex.axis=1.5)
axis(2,at=c(0:6)*5000,label=paste0(c(0:6)*5,"K"))
abline(v=17.5)
#title(main=" ")


lines(sum2014_47$monthindex,sum2014_47$medviews,col="red",type="b",lty=2,lwd=
3)
lines(sum2014_31$monthindex,sum2014_31$medviews,col="blue",type="b",lty=4,lwd
=3)

abline(h=(1:6)*5000,lty=3)

legend(24,19500,legend=c("Terror 48","Terror 48 without Hamas","High Privacy
31"),text.col=c("darkgreen","red","blue"),cex=1.5)
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/","terror48_2014
medianviews.png"),type="png")

######################################
# End mean and median 48 plots
######################################

######################################
# now do all 48 articles individually
######################################
for (i in 1:48) {
tmpplot<-art48incl2018[art48incl2018$artnum==i,]
tmpname<-unique(tmpplot$artname)
plot(tmpplot$monthindex,tmpplot$pageviewall,main=paste("Page Views
for",tmpname),col="blue",type="b",lwd=2,axes=F,xlab="",ylab="Monthly Page
Views")
axis(1,at=tmpplot$monthindex,label=tmpplot$dateabbr,las=2)
axis(2,at=1000*pretty(tmpplot$pageviewall/1000),label=paste0(pretty(tmpplot$p
ageviewall/1000),"K"),las=2)
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/graphs/","indivg
rph_",tmpname,".png"),type="png")
# just first 32
tmpplot<-art48incl2018[art48incl2018$artnum==i &
art48incl2018$monthindex<=32,]
tmpname<-unique(tmpplot$artname)
plot(tmpplot$monthindex,tmpplot$pageviewall,main=paste("Page Views
for",tmpname),col="blue",type="b",lwd=2,axes=F,xlab="",ylab="Monthly Page
Views")
axis(1,at=tmpplot$monthindex,label=tmpplot$dateabbr,las=2)
axis(2,at=1000*pretty(tmpplot$pageviewall/1000),label=paste0(pretty(tmpplot$p
ageviewall/1000),"K"),las=2)
abline(v=17.5,lwd=2)
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/graphs/","indiv3
2grph_",tmpname,".png"),type="png")
}

# infrastructure plots
infranames<-names(compinfra34)
for (i in 1:34) {
tmpploty<-compinfra34[,i+4]
tmpname<-infranames[i+4]
plot(1:32,tmpploty,main=paste("Infrastructure: Page Views
for",tmpname),col="blue",type="b",lwd=2,axes=F,xlab="",ylab="Monthly Page
Views")
axis(1,at=1:32,label=labelshort,las=2)
axis(2,at=1000*pretty(tmpploty/1000),label=paste0(pretty(tmpploty/1000),"K"),
las=2)
abline(v=17.5,lwd=2)
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/graphs/","infra3
4_",tmpname,".png"),type="png")
}
# security plots

securitynames<-names(compsec25)
for (i in 1:25) {
tmpploty<-compsec25[,i+4]
tmpname<-securitynames[i+4]
plot(1:32,tmpploty,main=paste("Security: Page Views
for",tmpname),col="blue",type="b",lwd=2,axes=F,xlab="",ylab="Monthly Page
Views")
axis(1,at=1:32,label=labelshort,las=2)
axis(2,at=1000*pretty(tmpploty/1000),label=paste0(pretty(tmpploty/1000),"K"),
las=2)
abline(v=17.5,lwd=2)
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/graphs/","sec25_
",tmpname,".png"),type="png")
}
```

```
# popular plots

popnames<-names(comppop26)
for (i in 1:26) {
tmpploty<-comppop26[,i+4]
tmpname<-popnames[i+4]
plot(1:32,tmpploty,main=paste("Popular: Page Views
for",tmpname),col="blue",type="b",lwd=2,axes=F,xlab="",ylab="Monthly Page
Views in Millions")
axis(1,at=1:32,label=labelshort,las=2)
axis(2,at=1000000*pretty(tmpploty/1000000),label=paste0(pretty(tmpploty/10000
00),"MM"),las=2)
abline(v=17.5,lwd=2)
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/graphs/","pop26_
",tmpname,".png"),type="png")
}

# multiple per page first 32 months
# just first 32
par(mfrow=c(4,3))
for (i in 1:48) {
tmpplot<-art48incl2018[art48incl2018$artnum==i &
art48incl2018$monthindex<=32,]
tmpname<-unique(tmpplot$artname)
plot(tmpplot$monthindex,tmpplot$pageviewall,main=paste("Page Views
for",tmpname),col="blue",type="b",lwd=2,axes=F,xlab="",ylab="Monthly Page
Views")
axis(1,at=tmpplot$monthindex,label=tmpplot$dateabbr,las=2)
axis(2,at=1000*pretty(tmpplot$pageviewall/1000),label=paste0(pretty(tmpplot$p
ageviewall/1000),"K"),las=2)
abline(v=17.5,lwd=2)
if (trunc(i/12)==i/12) {
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/graphs/","mfrow4
3_32grph_",i,".png"),type="png")
}
}
# show top four in terms of page views
par(mfrow=c(2,2))
top4<-c("Pakistan","Iran","Nigeria","Afghanistan")
for (i in 1:4) {
tmpplot<-art48incl2018[art48incl2018$artname==top4[i] &
art48incl2018$monthindex<=32,]
tmpname<-unique(tmpplot$artname)
plot(tmpplot$monthindex,tmpplot$pageviewall,main=paste("Page Views
for",tmpname),col="blue",type="b",lwd=2,axes=F,xlab="",ylab="Monthly Page
Views")
axis(1,at=tmpplot$monthindex,label=tmpplot$dateabbr,las=2)
axis(2,at=1000*pretty(tmpplot$pageviewall/1000),label=paste0(pretty(tmpplot$p
ageviewall/1000),"K"),las=2)
abline(v=17.5,lwd=2)
}
savePlot(paste0("D:/clients_2018/DOJ_Wiki_NSA/programsdata/R/graphs/","top4_3
2grph_",i,".png"),type="png")


par(mfrow=c(1,1))

#library(dplyr)
# indiv
tmpcol=rep(c("black","darkgreen","blue","green","magenta","orange","mediumorc
hid1","red"),8)
tmpplot<-art48incl2018[art48incl2018$artnum==1 &
art48incl2018$monthindex<=32,]

plot(tmpplot$monthindex,tmpplot$pageviewall,main=paste("
"),col=tmpcol[1],type="b",axes=F,xlab="",ylab="Monthly Page
Views",ylim=c(0,600000),lwd=2)
axis(1,at=tmpplot$monthindex,label=tmpplot$dateabbr,las=2)
axis(2,at=c(0:6)*100000,label=c("0",paste0(1:5,"00K"),">600K"),las=2)

for (i in 2:48) {
tmpplot<-art48incl2018[art48incl2018$artnum==i &
art48incl2018$monthindex<=32,]
tmpplot$pageviewall[tmpplot$pageviewall>600000]<-600000
tmpname<-unique(tmpplot$artname)
lines(tmpplot$monthindex,tmpplot$pageviewall,type="b",col=tmpcol[i],lwd=2)
}
savePlot("all48inonegraph.png",type="png")

#
# Figure 2
plot(sum2014_47$monthindex,sum2014_47$meanviews*47,main=paste("
"),type="b",axes=F,xlab="",ylab="Monthly Page
Views",ylim=c(1500000,3500000),lwd=2,col="red",cex.lab=1.2)
axis(1,at=sum2014_47$monthindex,label=tmpplot$dateabbr,las=2,cex.axis=1.3)
axis(2,at=1000000*c(1.5,2.0,2.5,3.0,3.5),label=c("1.5MM","2.0MM","2.5MM","3.0
MM","3.5MM"),las=2,pos=c(.8,1500000),cex.axis=1.2)
abline(v=17.5,lwd=2)
savePlot("Penneyfig2.png",type="png")
```

## APPENDIX II: Documents Considered

1. *Dkt 186-6_Declaration of Jonathon Penney.pdf* ("Penney Declaration")
2. *English Homepage Views (Raw - Non-Mobile).xlsx* – Provided to me as data underlying the Penney Declaration analysis.
3. *Final 25 Article Security Comparator Data Set.xlsx* - Provided to me as data underlying the Penney Declaration analysis.
4. *Higher Privacy Rated Terrorism Articles (above 2) (31 Articles Set).xlsx* - Provided to me as data underlying the Penney Declaration analysis.
5. *IndependentPrivacyRatingResults-Full-Survey.pdf* – Provided to me as data underlying the Penney Declaration analysis.
6. *Infrastructure Security Comparator (34 Articles).xlsx* – Provided to me as data underlying the Penney Declaration analysis.
7. *Popular-Wikipedia-Pages-Comparator (26 Articles).xlsx* – Provided to me as data underlying the Penney Declaration analysis.
8. *Wikipedia Case Study - Key Variables.xlsx* – Provided to me as data underlying the Penney Declaration analysis.
9. *Wikipedia-Case-Study-Article-Traffic-June 2015-Full-48.xlsx* – Provided to me as data underlying the Penney Declaration analysis.
10. *Wikipedia-Case-Study-Article-Traffic-June 2015-Full-48_format_plus2018.xslx* – 48 Articles page views for months through 2018, which I compiled using the website referenced in my Declaration. I call these articles the Terror 48 in the body of my declaration.
11. *ISIS variations pageviews-20150701-20181130* – Article page views for ISIS, which I compiled using the website referenced in my Declaration.
12. Additional documents provided for consideration by the Department of Justice (but which I did not refer to in writing my Declaration).
    1. WIKI0001545.pdf
    2. WIKI0002024.pdf
    3. WIKI0002025.xlsx
    4. WIKI0002263.pdf
    5. WIKI0002274.pdf
    6. WIKI0002607.xlsx
    7. WIKI0002608.xlsx
    8. WIKI0004893.pdf
    9. WIKI0005137.pdf
    10. WIKI0005154.pdf
    11. WIKI0005174.pdf
    12. WIKI0005194.pdf
    13. WIKI0005229.pdf
    14. WIKI0005251.pdf
    15. WIKI0005266.pdf
    16. WIKI0005285.pdf
    17. WIKI0005300.pdf
    18. WIKI0005322.pdf

19. WIKI0005336.pdf
20. WIKI0005360.pdf
21. WIKI0005379.pdf
22. WIKI0005399.pdf
23. WIKI0005420.pdf
24. WIKI0005439.pdf
25. WIKI0005466.pdf
26. WIKI0005487.pdf
27. WIKI0005500.pdf
28. WIKI0005514.pdf
29. WIKI0005528.pdf
30. WIKI0005544.pdf
31. WIKI0005577.pdf
32. WIKI0005693.pdf
33. WIKI0005832.pdf
34. WIKI0005978.pdf
35. WIKI0006146.xlsx
36. WIKI0006147.xlsx
37. WIKI0006148.xlsx
38. WIKI0006149.xlsx
39. WIKI0006282.csv
40. WIKI0006283.pdf
41. WIKI0006295.xlsx
42. WIKI0006296.pdf
43. WIKI0006367.xlsx
44. WIKI0006368.csv
45. WIKI0006369.pdf
46. WIKI0007358.pdf
47. WIKI0007616.xlsx
48. WIKI0008237.pdf
49. WIKI0008262.pdf
50. WIKI0008271.xlsx
51. WIKI0008312.csv
52. WIKI0008313.csv
53. WIKI0009301.csv
54. WIKI0009302.xlsx

# APPENDIX III: Resume and Testimony History

**Resume of Alan J. Salzberg**

## EXPERIENCE

**Salt Hill Statistical Consulting, Founder and Principal, 2000-present**
Founder and Principal of a statistical consulting company (formerly Quantitative Analysis). The firm is skilled at presenting complex ideas to non-experts, including providing expert testimony in court settings. Capabilities include development and implementation of statistical techniques as well as critical review and audit of existing statistical estimates, samples, and models. The company's clients are law firms, government, and private corporations and have included: United States Department of Labor; Pfizer; Barnes & Thornburg; Honeywell; K&L Gates; City of New York.

**Summit Consulting, Teaming Partner, 2009-present**
Consult on multiple engagements with economic consulting firm on large-scale government projects. Served as a Director at the firm in 2014.

**Analysis & Inference, Inc., CEO, 1991-1995 and 2008-2013**
Led a statistical consulting company that provides consulting services to corporations, law firms, and government.

**KPMG LLP, Practice Leader, Quantitative Analysis Group – New York, 1996-2000**
Established and led the New York office of KPMG's Quantitative Analysis Group.
**Morgan Stanley, Associate, 1988-1990, 1995-1996**
Performed statistical modeling and software design.

## EDUCATION

**Ph.D., Statistics**, Wharton School, University of Pennsylvania, 1995
**M.A., Statistics**, Wharton School, University of Pennsylvania, 1992
**B.S., Economics** (concentration in Economics and Finance), *cum laude,* Wharton School, University of Pennsylvania, 1988

## ENGAGEMENTS

- Served as a statistical consultant on behalf of the United States government and other entities in the development of dynamic models for residential property valuation in order to determine whether certain residential mortgage-backed securities (RMBS) were fairly valued. Made use of statistical and econometric techniques including regression modeling, statistical sampling, bootstrapping, and bias adjustment.

- Using social security and insurance company data, developed two probability-based models in order to match unclaimed assets with the individual owners of those assets. The models were successfully implemented at our client, a financial services company, and used to assist state agencies in locating unclaimed assets.

- Served as a statistical expert on behalf of a nuclear power plant owner in a construction delay dispute. Analyzed a statistical sample and model from a population of more than 100,000 comments on design documents. Authored three expert reports and testified before the International Chamber of Commerce's arbitration court in London.

- Served as a statistical sampling expert on behalf of an arbitration panel in a dispute regarding payments on several thousand healthcare claims. Analyzed data from samples of those claims and made recommendations to the arbitration panel regarding proper interpretation and extrapolation of the sample.

- On behalf of the New York State Office of Medicaid Inspector General, reviewed the sampling and estimation methodology used to audit Medicaid providers in New York State. Reviewed and critiqued specific methodologies in ongoing matters, and provided recommendations for improving the statistical audit process.

- On behalf of a Fortune 100 company, evaluated models that estimated the potential liability in more than 10,000 asbestos settlements. In addition, reviewed the likely bias and other issues with a model that predicted the "propensity to sue" for future claims. Wrote two expert reports concerning findings and testified as a statistical expert regarding those findings.

- In a series of matters on behalf of the law department for a major city, created and analyzed a massive real estate database, modeled market and sales values, and wrote expert reports to determine potential biases of alternative methods of valuing commercial real estate. Determined the validity of assumptions about lease lengths, turnover rates, and other issues affecting rents and property values. Testified as a statistical expert in one of these matters.

- On behalf of the United States Department of Labor, acted as the principal investigator on a study of industry compliance with certain labor laws. Developed and pulled a statistical sample for evaluation. Performed survival analysis to better understand how long certain industry investigations would last and the likely outcomes of such investigations.

- For major pharmaceutical company, analyzed company and external marketing data to determine reliability and potential biases in using external data sources. Analyzed physician-specific data for a period of 36 months concerning product marketing to approximately 1 million prescription drug subscribers.

- In complex litigation matter involving an undersea oil field, analyzed data from several years of inspections and repairs to determine likelihood of a catastrophic failure that would result in a major oil spill. Used survival analysis to determine the likelihood of such an event for different inspection and repair cycles.

- On behalf of several state public service commissions, directed data analysis and statistical design in a series of tests of Bell South, Verizon, SBC-Ameritech, and Qwest. Beginning in

1998, developed software and procedures for calculating performance metrics and evaluating the competitive environment. Testified before several state public service commissions, including New York, Virginia, Florida, Michigan, and Colorado.

- Modeled television audience ratings to determine the Public Broadcasting System's share of cable royalty distributions. Used statistical methods to determine a reliable estimate of PBS's cable royalty share. The estimate resulted in a multi-million dollar decision in favor of the Public Broadcasting System by the Cable Royalty Tribunal.

- Lead statistician in the design and implementation of a sample of all personal property and equipment on behalf of the United States Internal Revenue Service. The population of interest involved more than one million items contained in over 1,000 buildings. The sample design, implementation, and resulting estimates and projections were subject to intense scrutiny by the United States General Accounting Office.

- For the United States Department of Justice, designed and implemented a sample to estimate the number of immigrants improperly granted citizenship. The sample was designed to provide precision of plus or minus less than 1%, for a population of more than 1 million immigrants. The work was the focus of intense congressional scrutiny and received substantial review in the media.

- On behalf of Fortune 100 company, created statistical models to determine the probabilities and likely severities of accidents for different employee and accident types. This project resulted in recommended annual savings of $3 million.

- On behalf of the Arava Institute of Environmental Studies, advised on design and sampling methodology for a broad-based survey of environmental education in middle and high schools. More than 7,000 students were surveyed in a sample that was stratified by size of town, income level, and other socio-economic variables. Performed weighted statistical analysis to project survey results to the population. Presented results before Israeli Congressional committee in July 2007.

- For the United States Customs Service (Department of Homeland Security), assisted with sampling of financial statement information. Designed and wrote sampling plans, helped implement the plans, and created spreadsheet calculator to analyze results. In an earlier engagement, evaluated the credibility of statistical sampling and analysis used to track and categorize imports, for the Office of Inspector General. Suggested improved methods of sampling and implementation.

- Provided expert testimony in statistics more than two dozen trials, hearings, and depositions over the last 20 years, including multiple times in United States Federal Court.

## RESEARCH

“What are the Chances?” blog, 2007 to present. Excerpts have been included in newspapers and textbooks, including Lundsford, Andrea L. and Ruszkiewicz, John, *Everything’s an Argument, 6th Edition*, 2012. The blog is publicly available at https://salthillstatistics.com/blog.

“Resolving a Multi-Million Dollar Contract Dispute with a Latin Square,” *American Statistician,* with William B. Fairley, Steven M. Crunk, Peter J. Kempthorne, Julie Novak, and Bee Leng Lee, 2017.

“Law and Statistics of Combining Categories: Wal-Mart and Employment Discrimination Cases”, with Albert J. Lee, *Proceedings of the 2010 Joint Statistical Meetings of the American Statistical Association*, 2010.

“Evaluating the Environmental Literacy of Israeli Elementary and High School Students,” with Maya Negev, Gonen Sagy, and Alon Tal, *Journal of Environmental Education*, Winter 2008.

“Trends in Environmental Education in Israel,” with Gonen Sagy, Maya Negev, Yaakov Garb, and Alon Tal, *Studies in Natural Resources and Environment,* Vol. 6, 2008. [In Hebrew]

“Results from a Representative Sample in the Israeli Educational System,” with Gonen Sagy, Maya Negev, Yaakov Garb, and Alon Tal, *Studies in Natural Resources and Environment,* Vol. 6, 2008. [In Hebrew]

“Comment on Local model uncertainty and incomplete-data bias by Copas and Li,” with Paul R. Rosenbaum, *Journal of the Royal Statistical Society, Series B*, 2005.

“Determining Air Exchange Rates in Schools Using Carbon Dioxide Monitoring”, with D. Salzberg and C. Fiegley, presented at the *American Industrial Hygiene Conference and Expo,* 2004.

“The Modified Z versus the Permutation Test in Third Party Telecommunications Testing”, *Proceedings of the 2001 Joint Statistical Meetings of the American Statistical Association*.

“Removable Selection Bias in Quasi-experiments," *The American Statistician,* May 1999.

"Skewed oligomers and origins of replication," with S. Salzberg, A. Kervalage, and J. Tomb, *Gene,* Volume 217, Issue 1-2 (1998), pp. 57-67.

"Selection Bias in Quasi-experiments," (Doctoral Thesis), 1995.

**Editorial Contributor** (referee for scholarly papers)**,** *American Statistician*.

***Patent*** *(#6,636,585)* One of five inventors on a patent for statistical process design related to information systems testing.

## PERSONAL

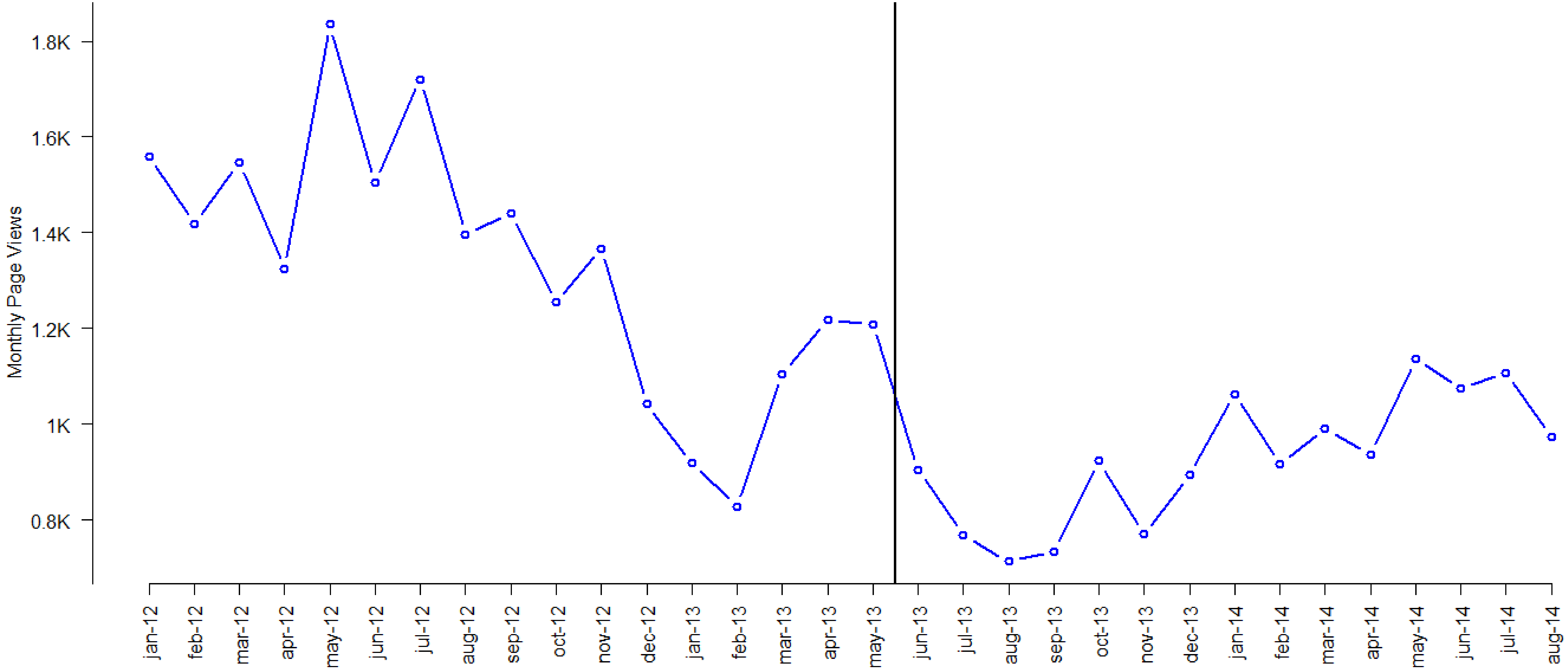
Married, with two daughters and a son.
Languages: English (native), Hebrew (conversational).
Member, Park Slope Food Coop.
Member, 39 Plaza Housing Corp (residential coop). Board member, 2012-2015.
Enjoy ultimate Frisbee, basketball, biking, hiking, running, tennis, chess, and bridge.

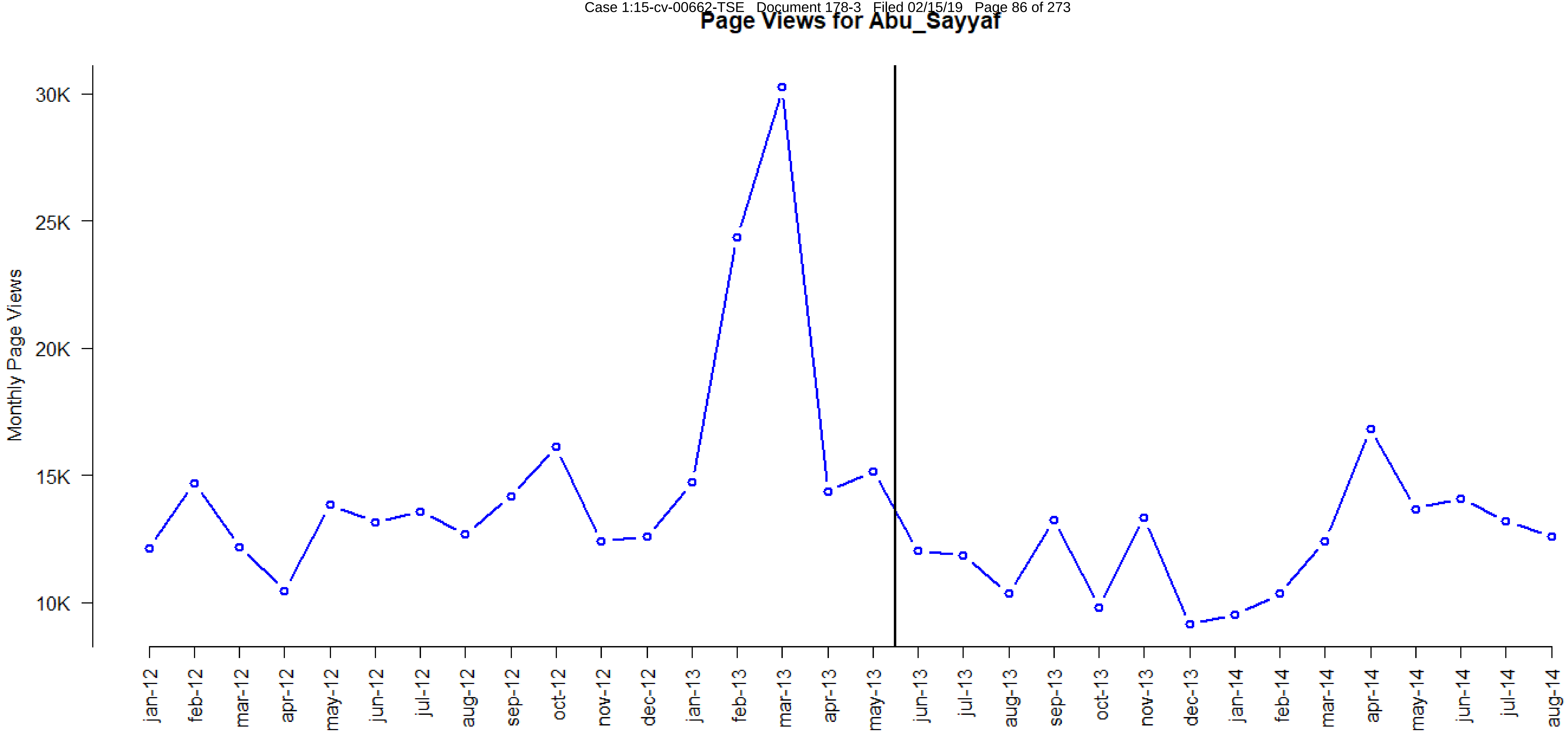
## FOUR YEAR TESTIMONY HISTORY

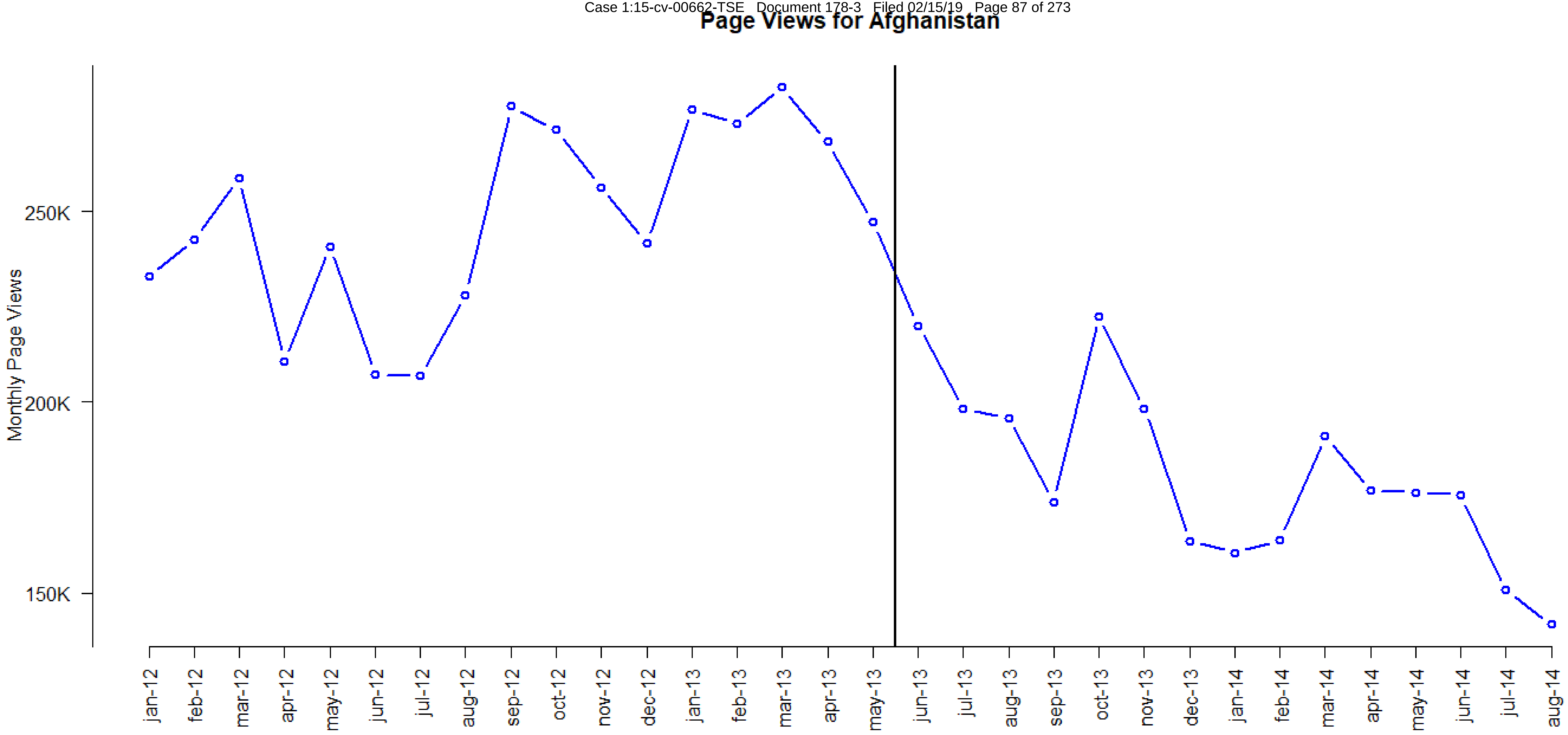
1. [Federal court] Bayer Healthcare LLC, v. Baxalta, et al, 2019.
2. [Federal court] Steward, et al, v. State of Texas, 2018.
3. [deposition] Center for Independence of the Disabled, et al, v. Metropolitan Transit Authority, et al, 2018.
4. [deposition] Bayer Healthcare, LLC, v. Baxalta Inc., et al, 2018.
5. [deposition] New Image Global, Inc. v. U.S., 2017.
6. [Federal court] Steward, et al, v. State of Texas, 2017.
7. [deposition] Home Equity Mortgage Trust, et al., v. DLJ Mortgage Capital, et al., 2017.
8. [court] Regents of the University of California v. County of Sacramento, 2016.
9. [international arbitration] Areva NP GmbH, Areva NP S.A.S. and Siemens Aktiengesellschaft v. Teollisuuden Voima Oyj, 2016.
10. [Federal court] Kerner v. City & County of Denver, 2015.
11. [deposition] Regents of the University of California v. County of Sacramento, 2015.

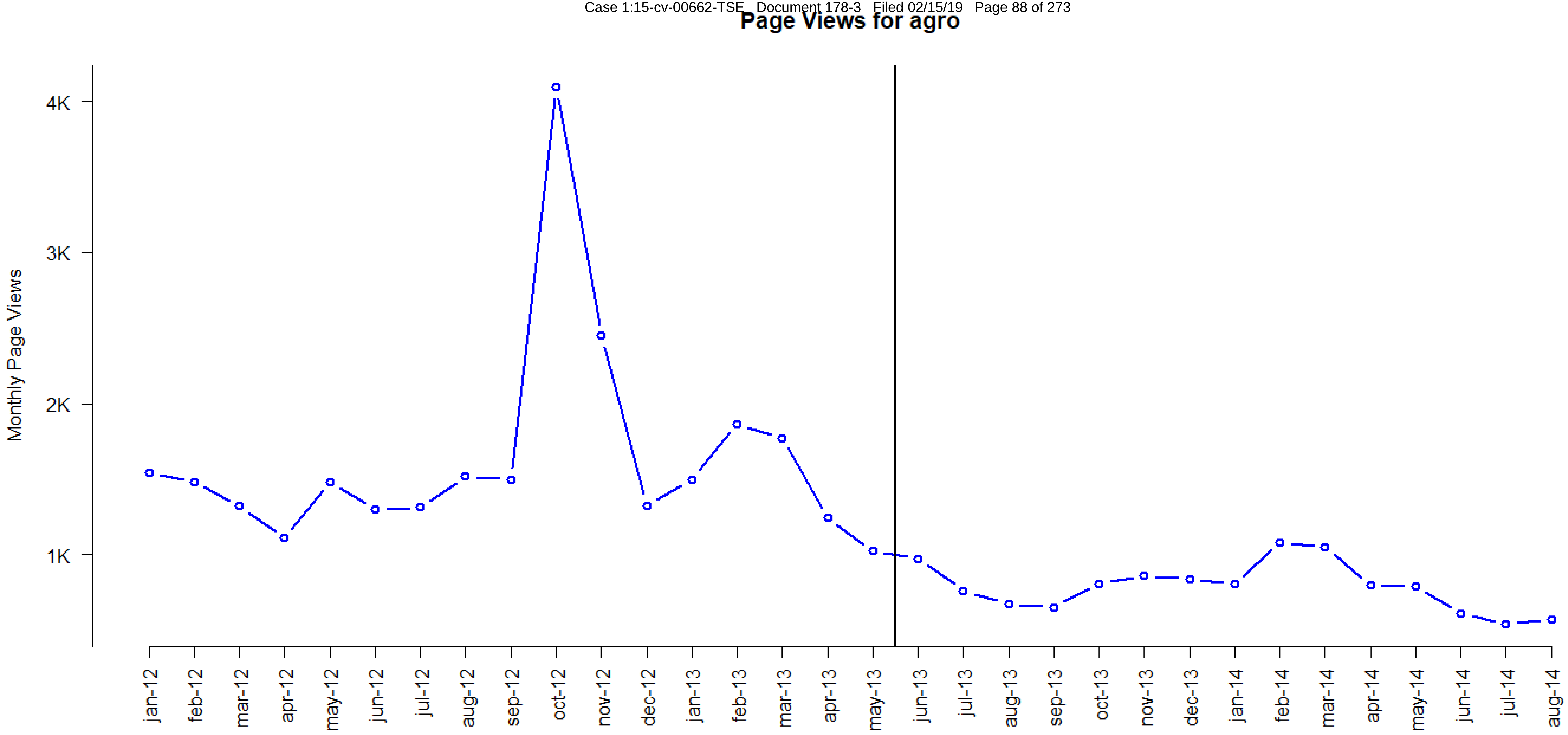
# APPENDIX IV: Page Views for 48 Terror Articles, Original Time Period

# Page Views for _Euskadi_ta_Askatasuna

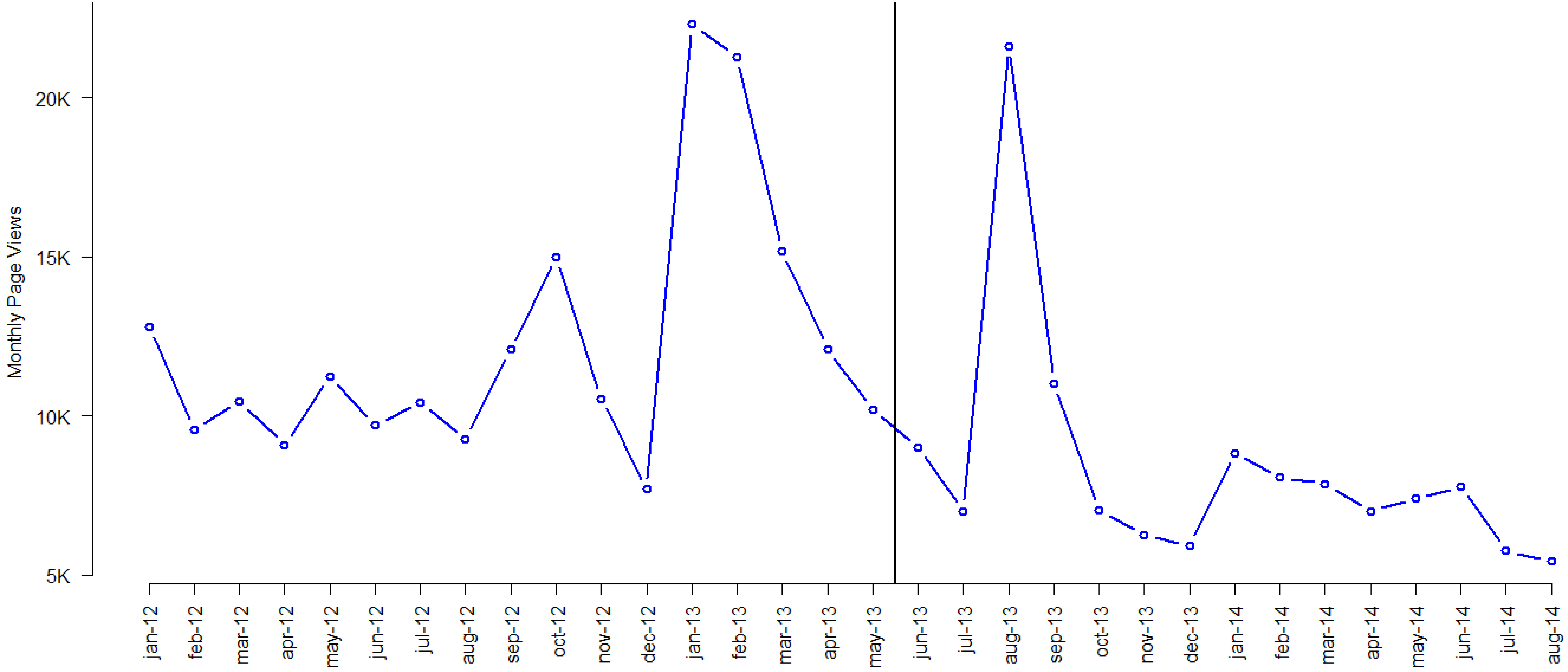



Page Views for Abu_Sayyaf
Monthly Page Views
30K
25K
20K
15K
10K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

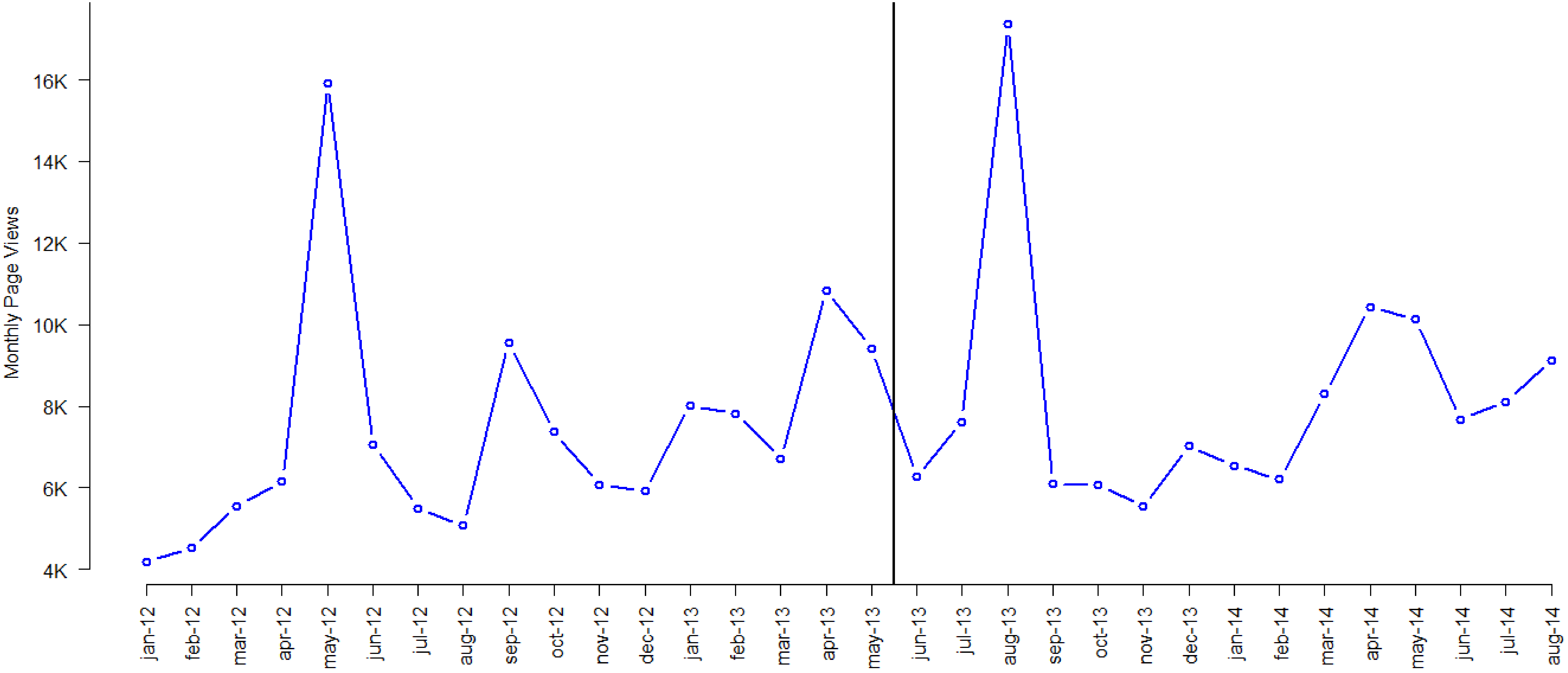

Page Views for Afghanistan
Monthly Page Views
250K
200K
150K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14


Page Views for agro
Monthly Page Views
4K
3K
2K
1K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

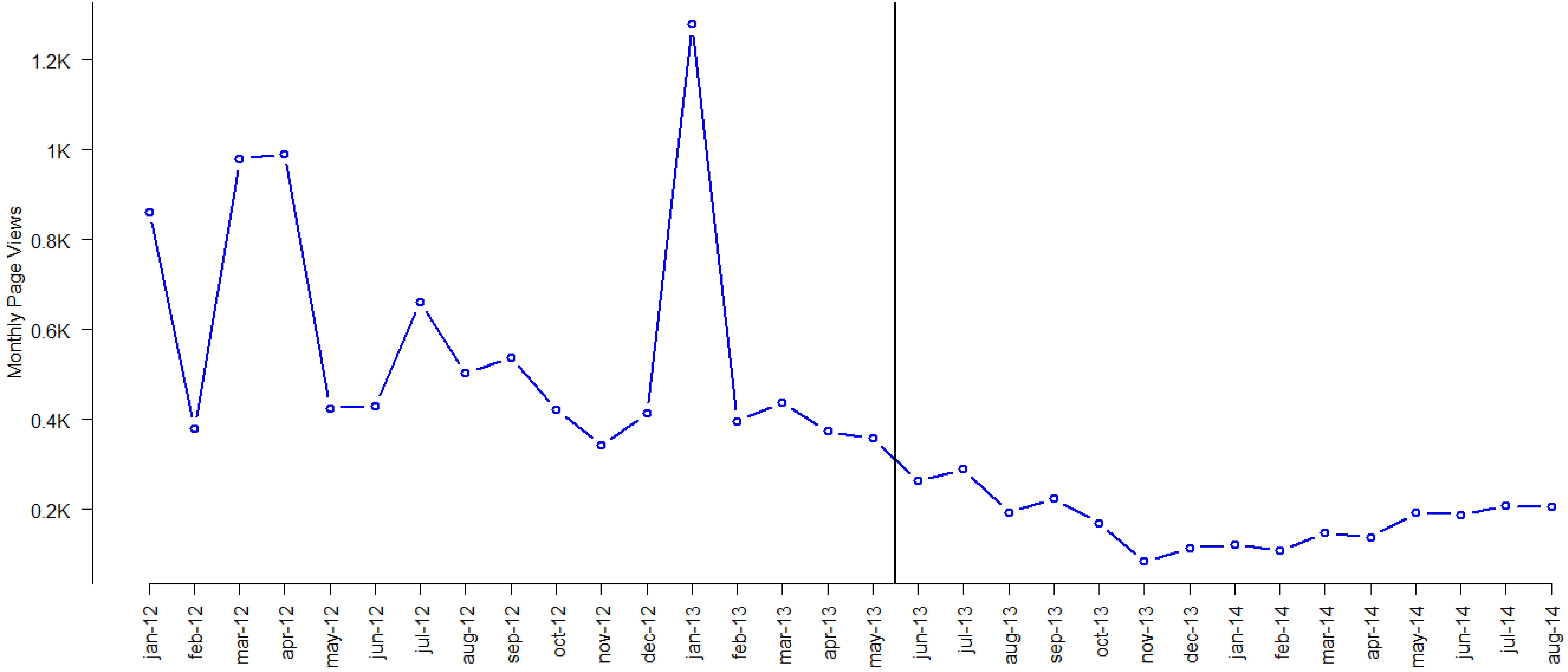
# Page Views for Al_Qaeda



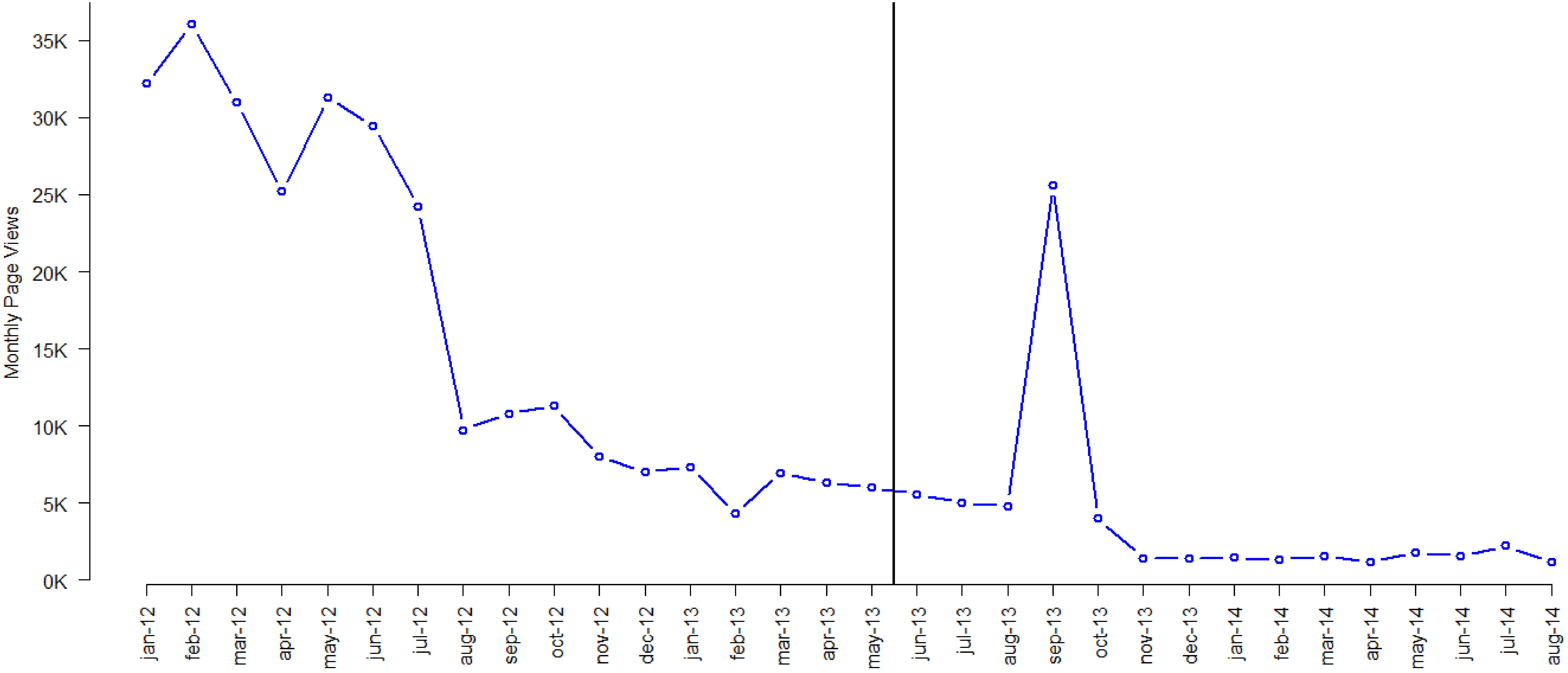
# Page Views for AL_Qaeda_in_the_Arabian_Peninsula

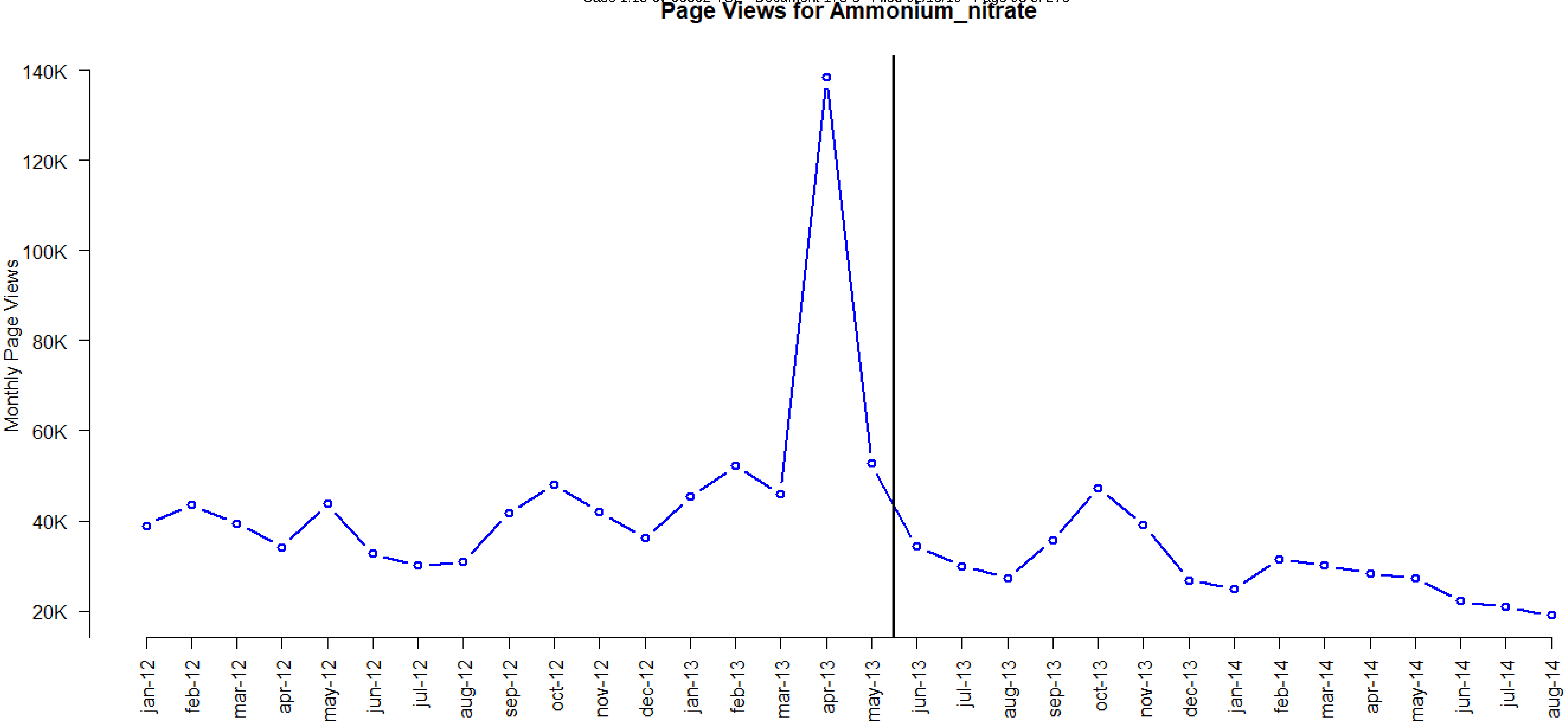


# Page Views for Al_Qaeda_in_the_Islamic_Maghreb



# Page Views for Al_Shabaab




Page Views for Ammonium_nitrate
Monthly Page Views
140K
120K
100K
80K
60K
40K
20K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
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feb-14
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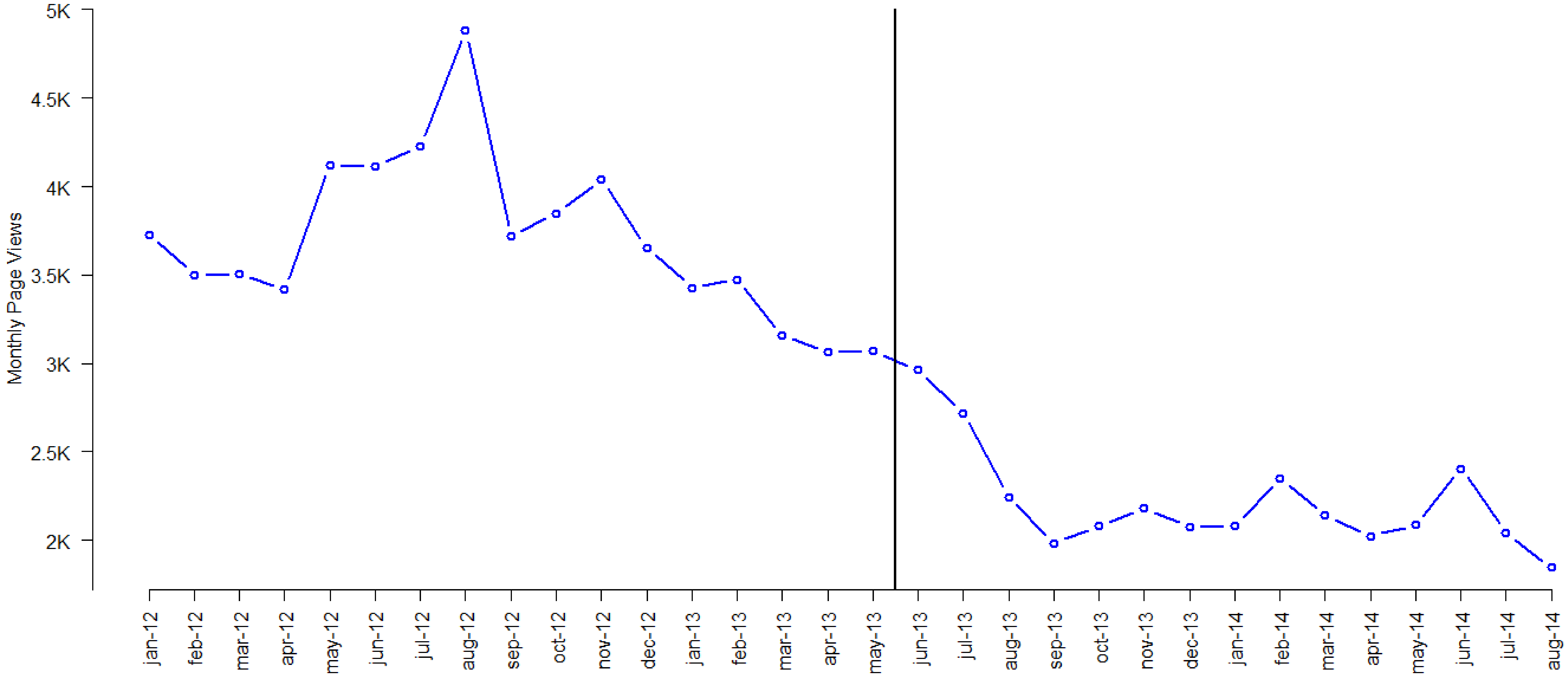
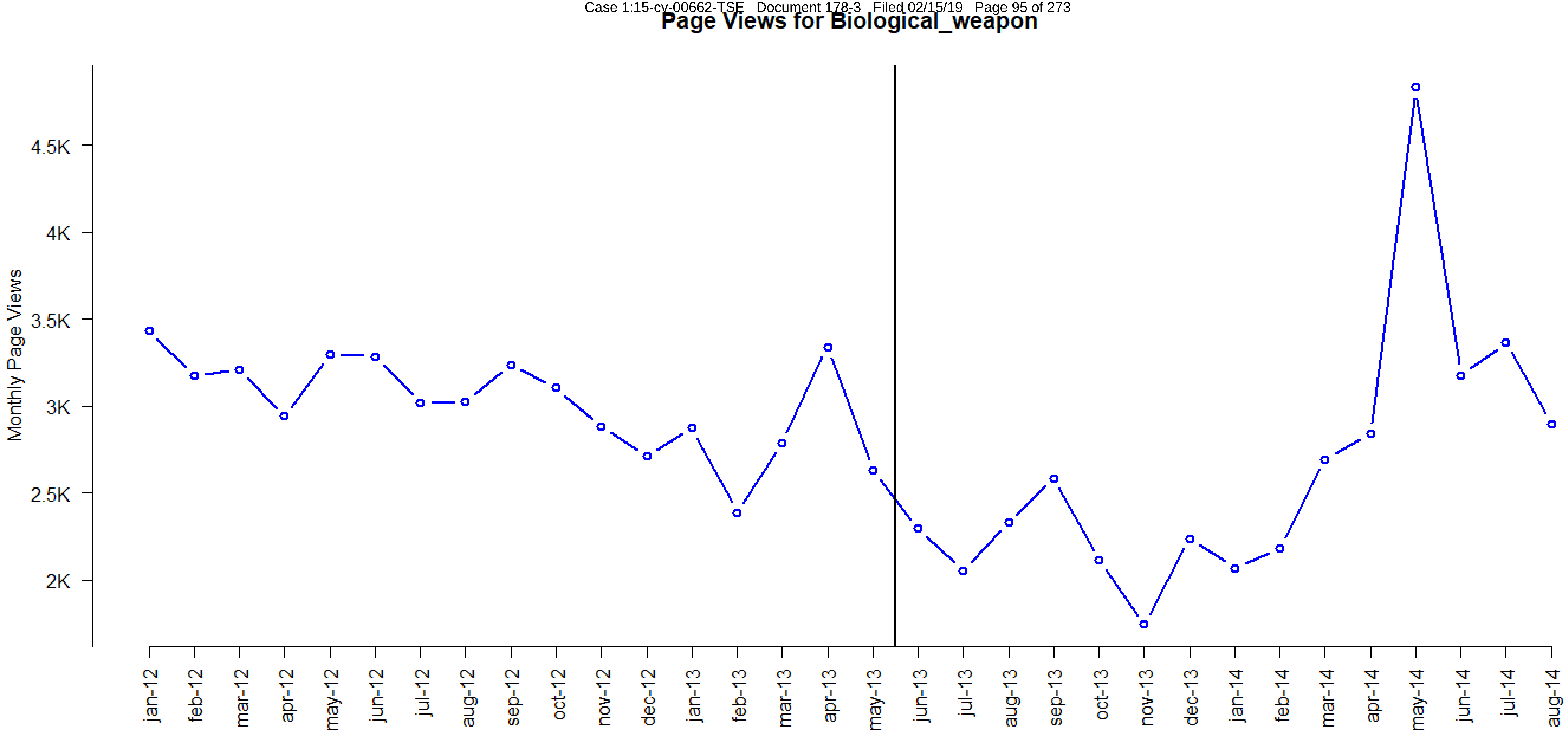
may-14
jun-14
jul-14
aug-14

## Page Views for attack




Page Views for Biological_weapon
Monthly Page Views
4.5K
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3.5K
3K
2.5K
2K
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mar-12
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may-12
jun-12
jul-12
aug-12
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oct-12
nov-12
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jul-13
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oct-13
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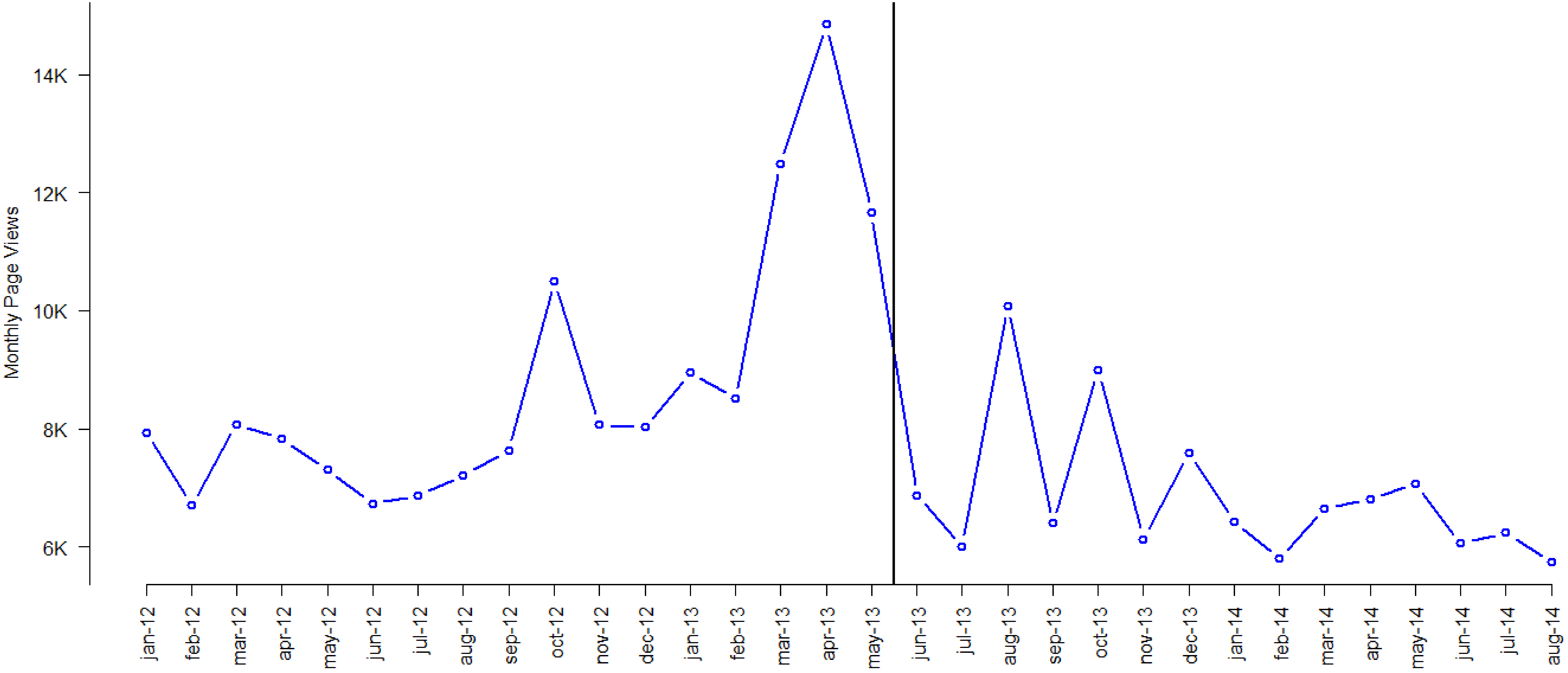
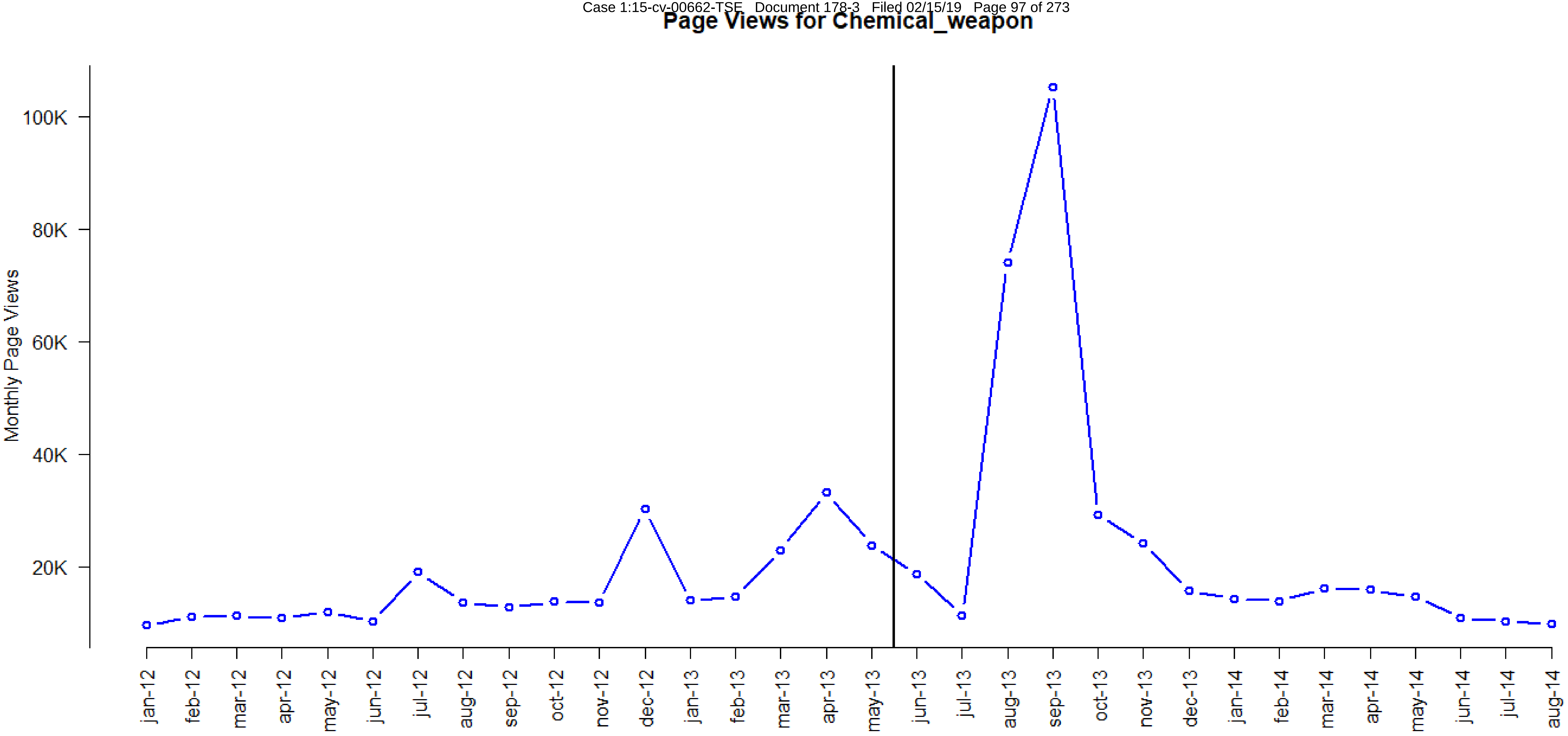
may-14
jun-14
jul-14
aug-14

## Page Views for Car_bomb




Page Views for Chemical_weapon
Monthly Page Views
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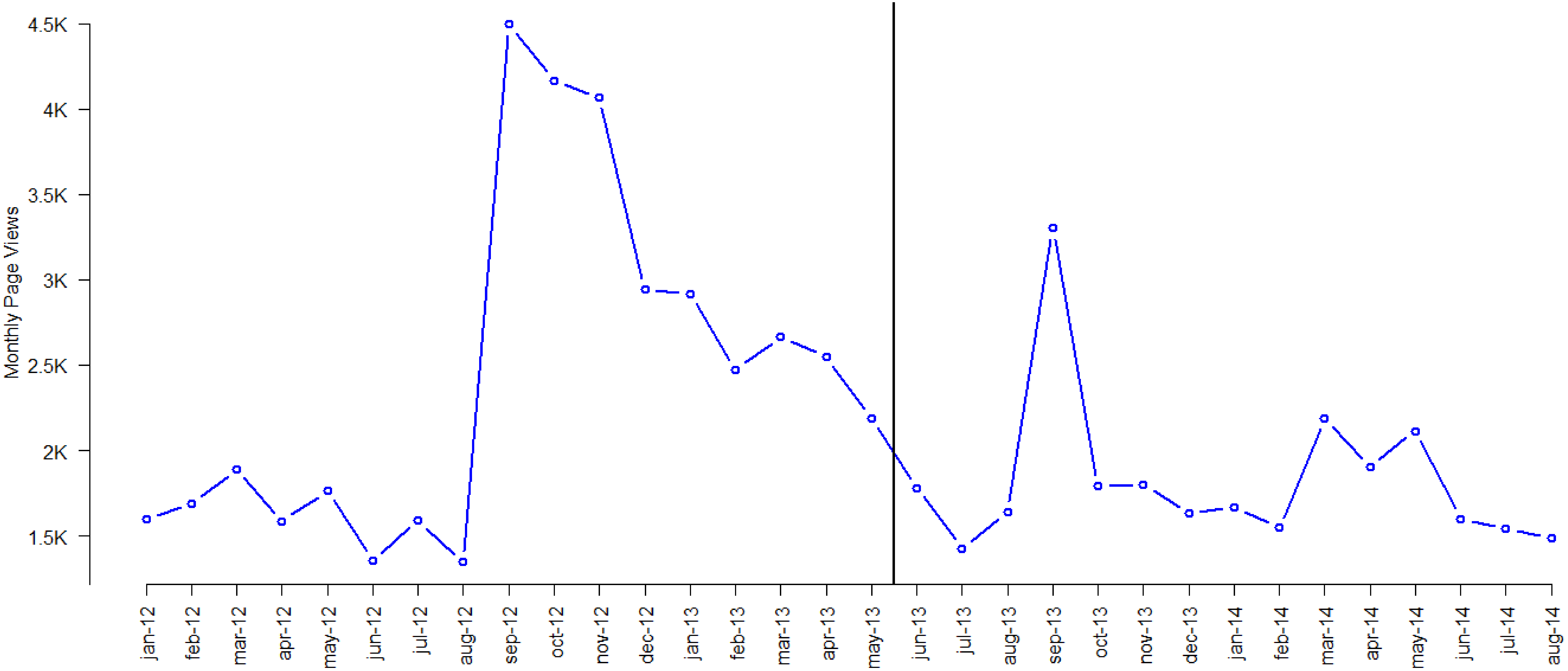
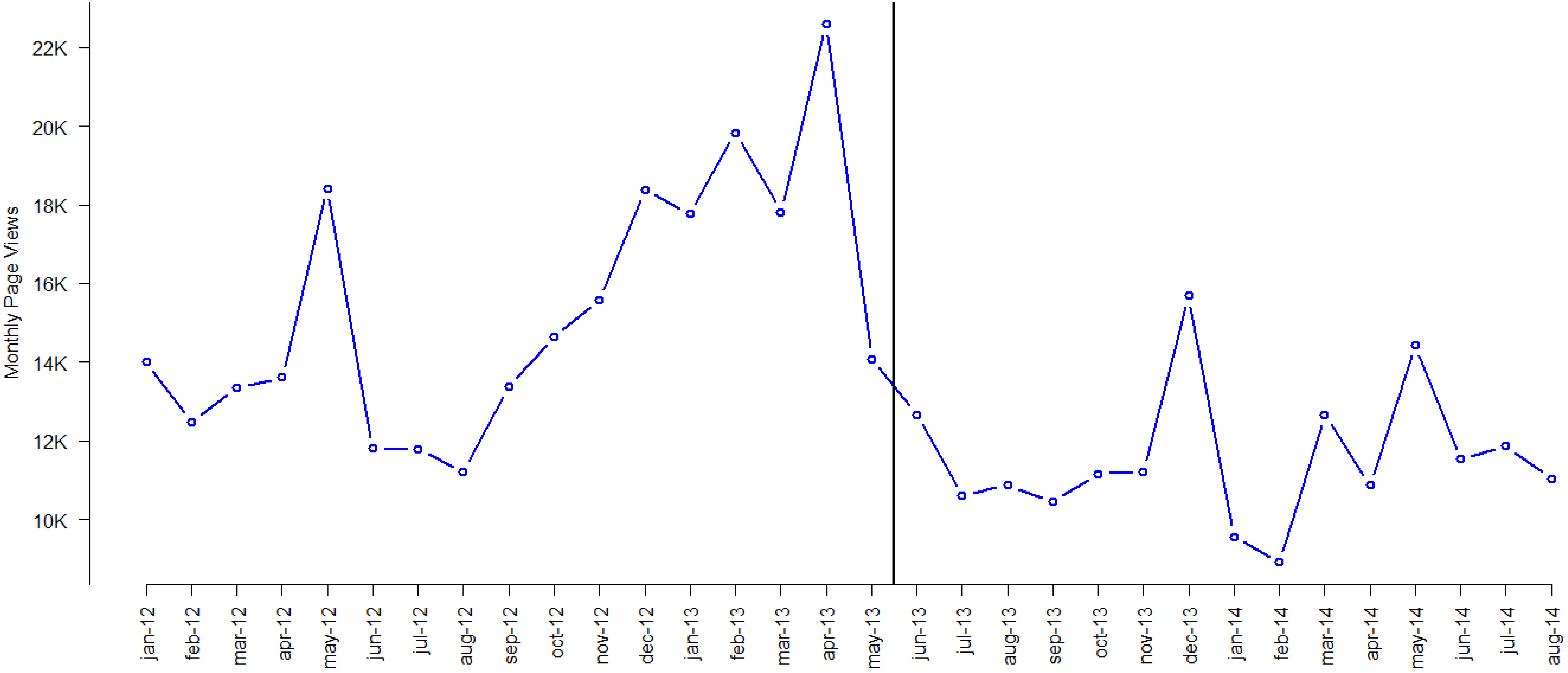
jul-14
aug-14

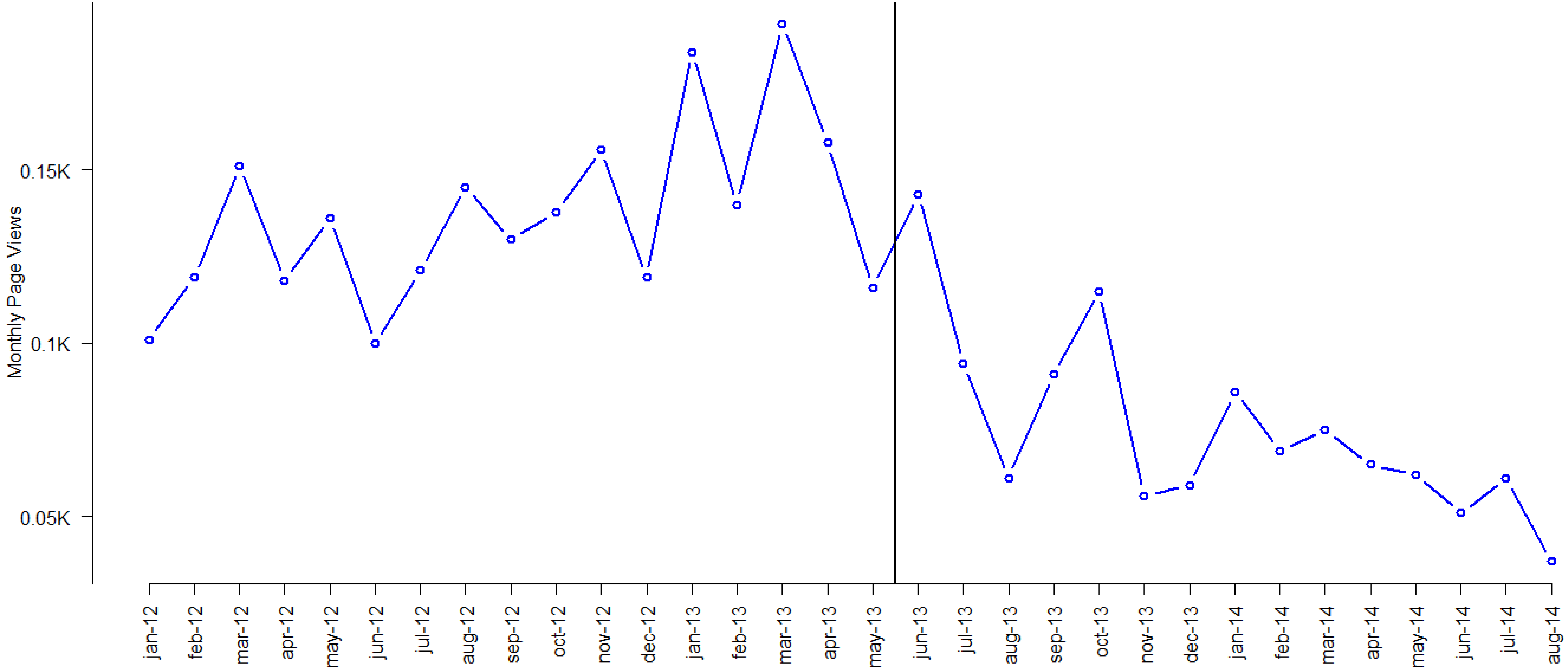
## Page Views for Conventional_weapon

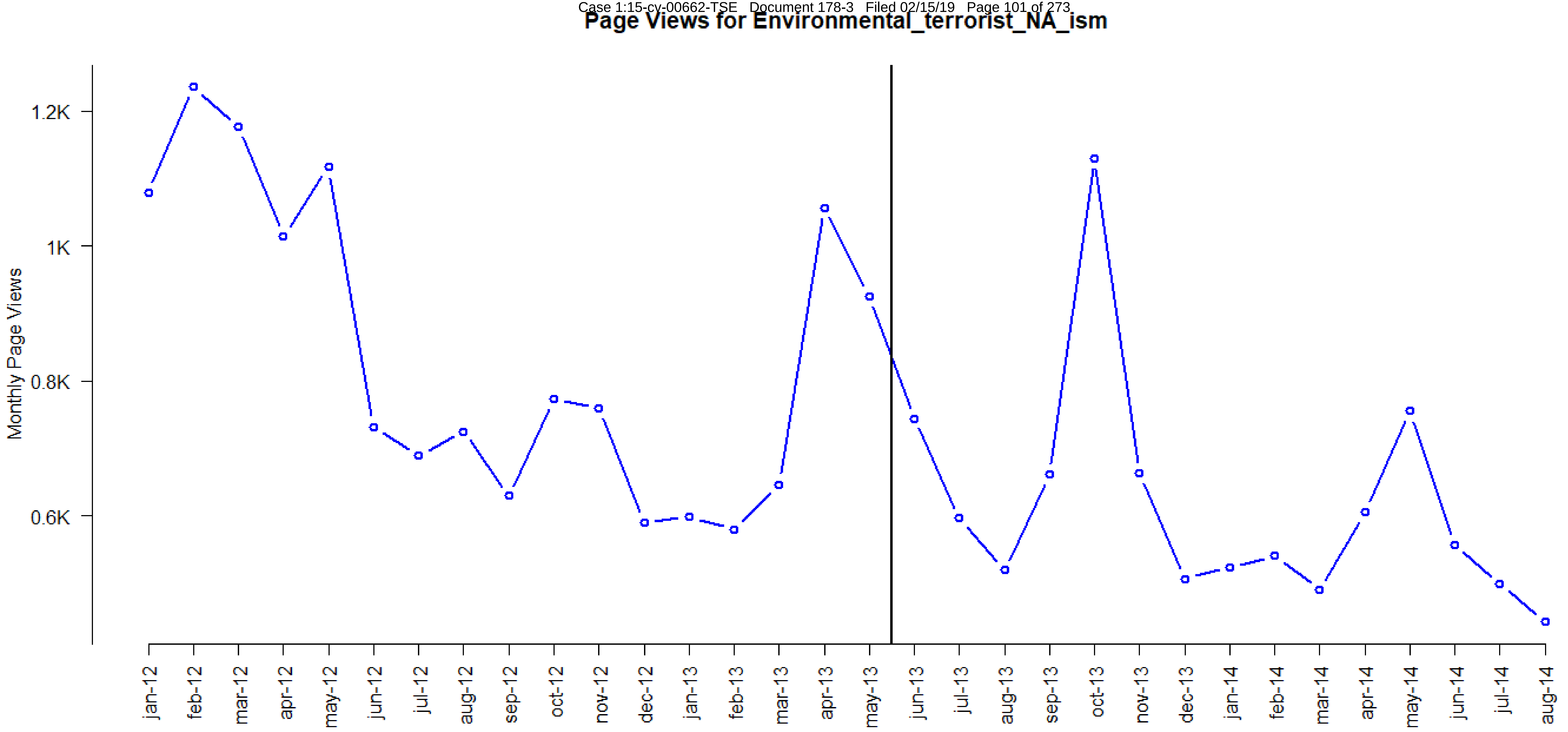


## Page Views for dirty_bomb



## Page Views for Eco_terrorism

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Monthly Page Views
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0.6K
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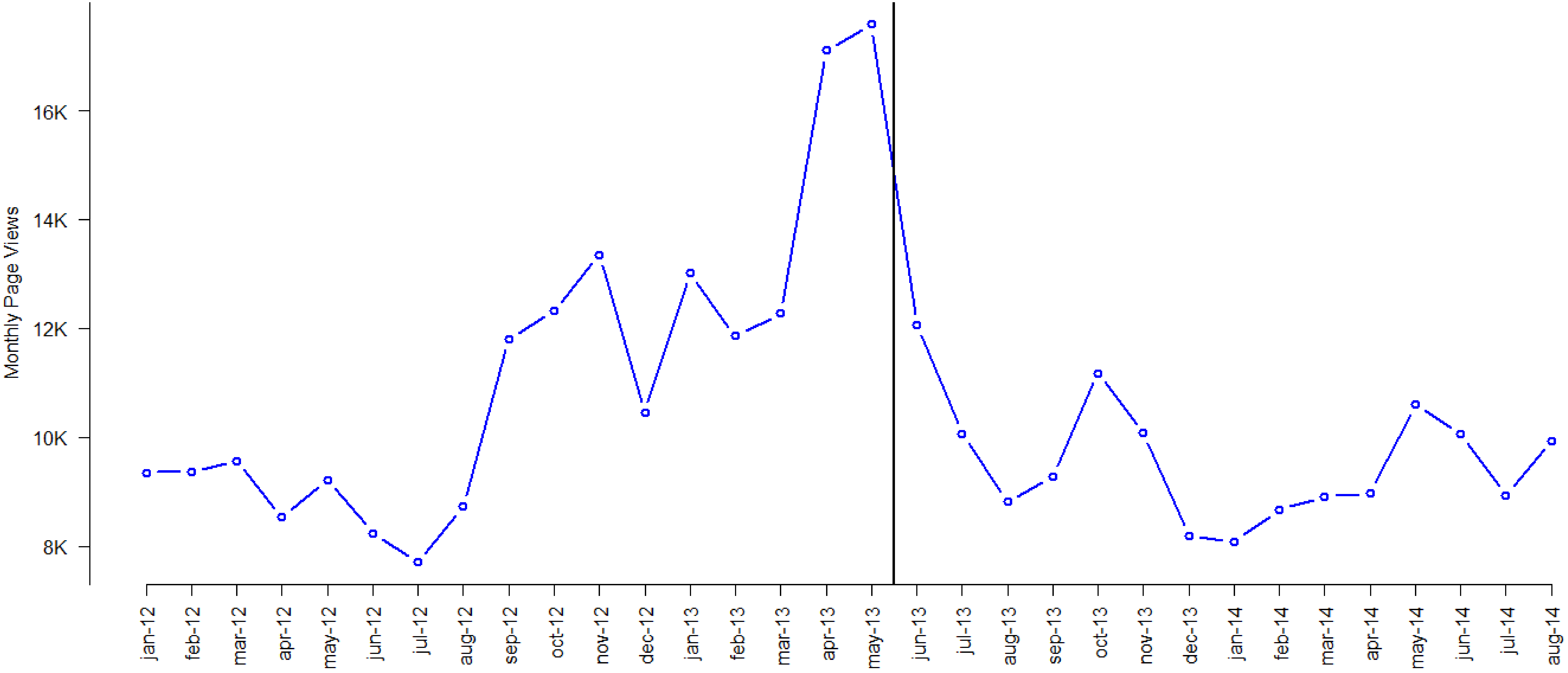
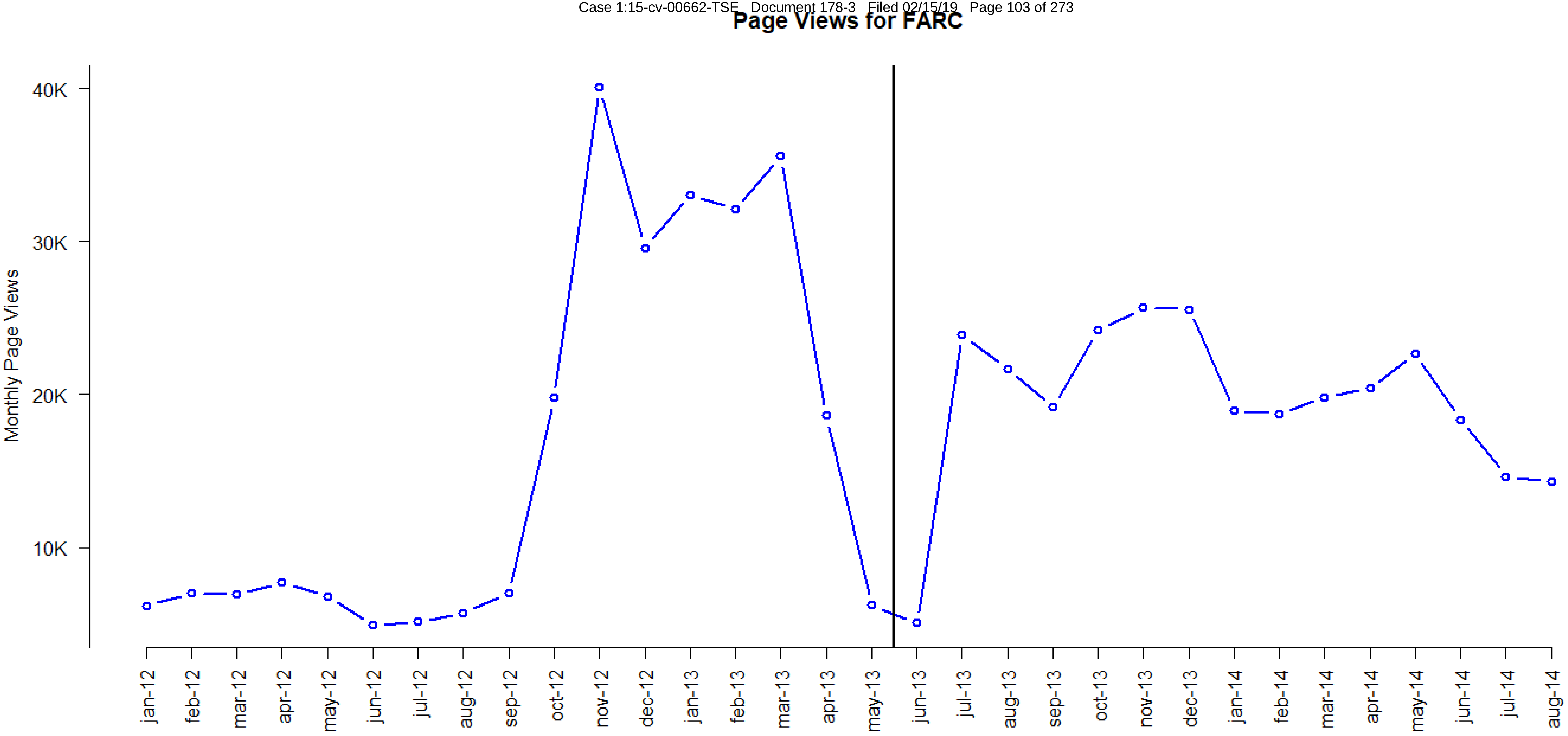
may-14
jun-14
jul-14
aug-14

## Page Views for Extremism




Page Views for FARC
Monthly Page Views
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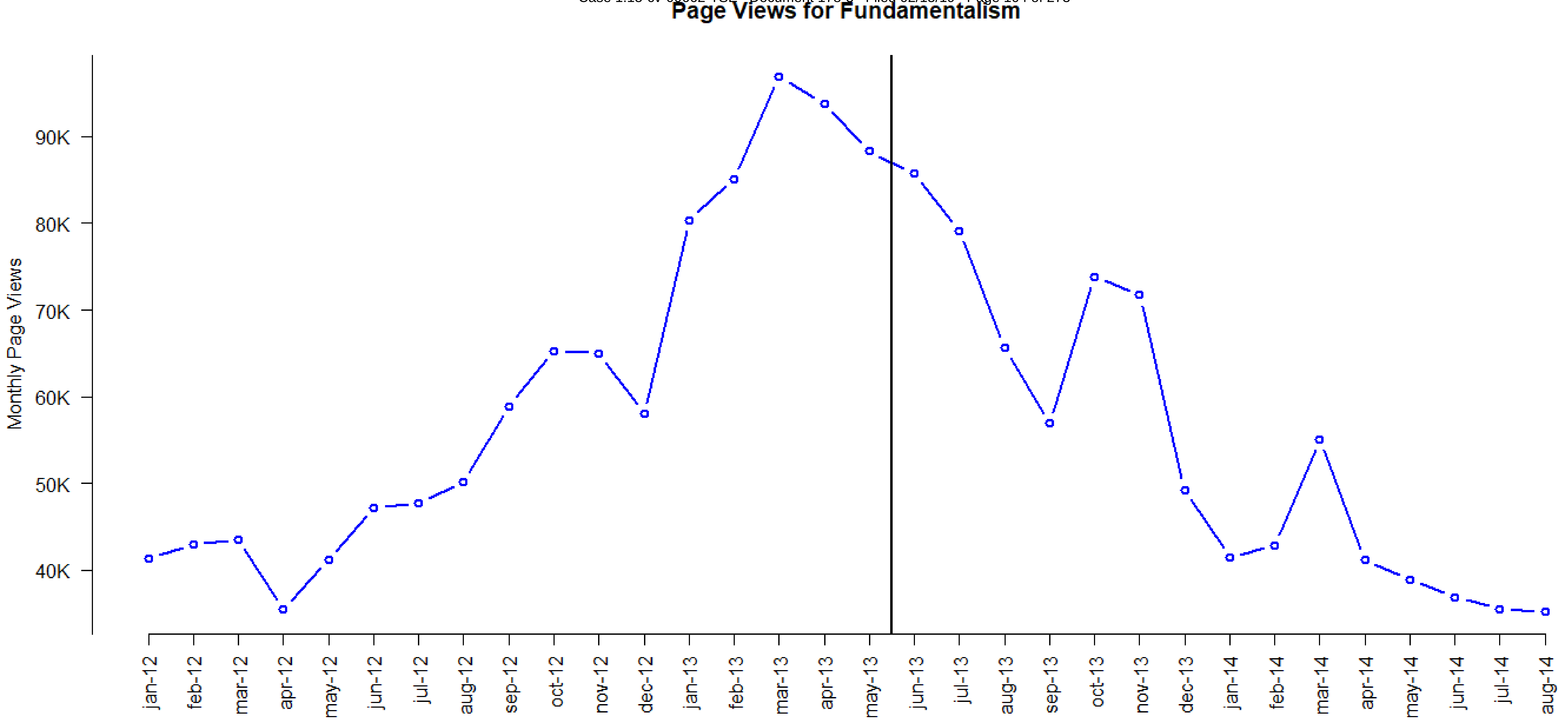
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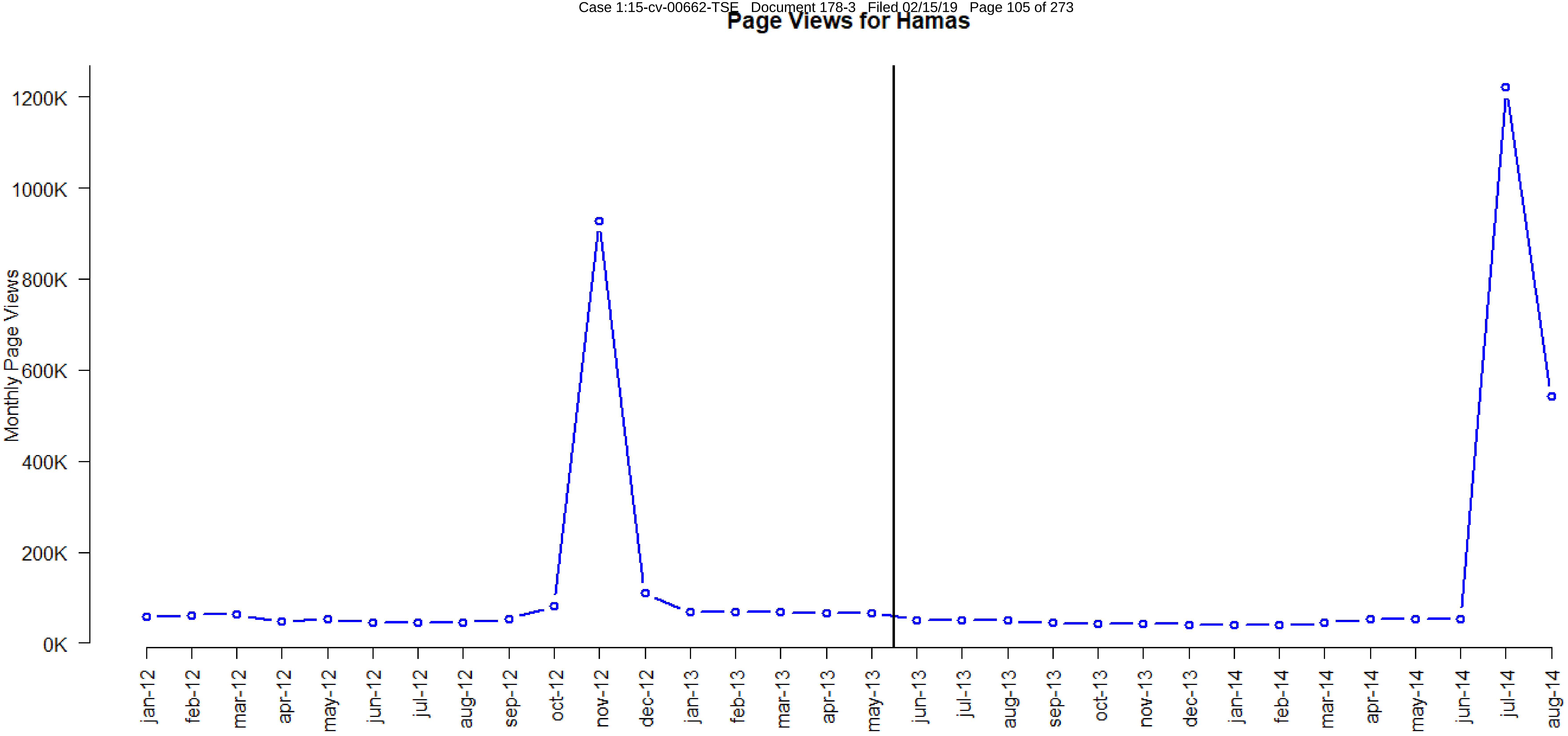
aug-14


Page Views for Hamas
Monthly Page Views
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1000K
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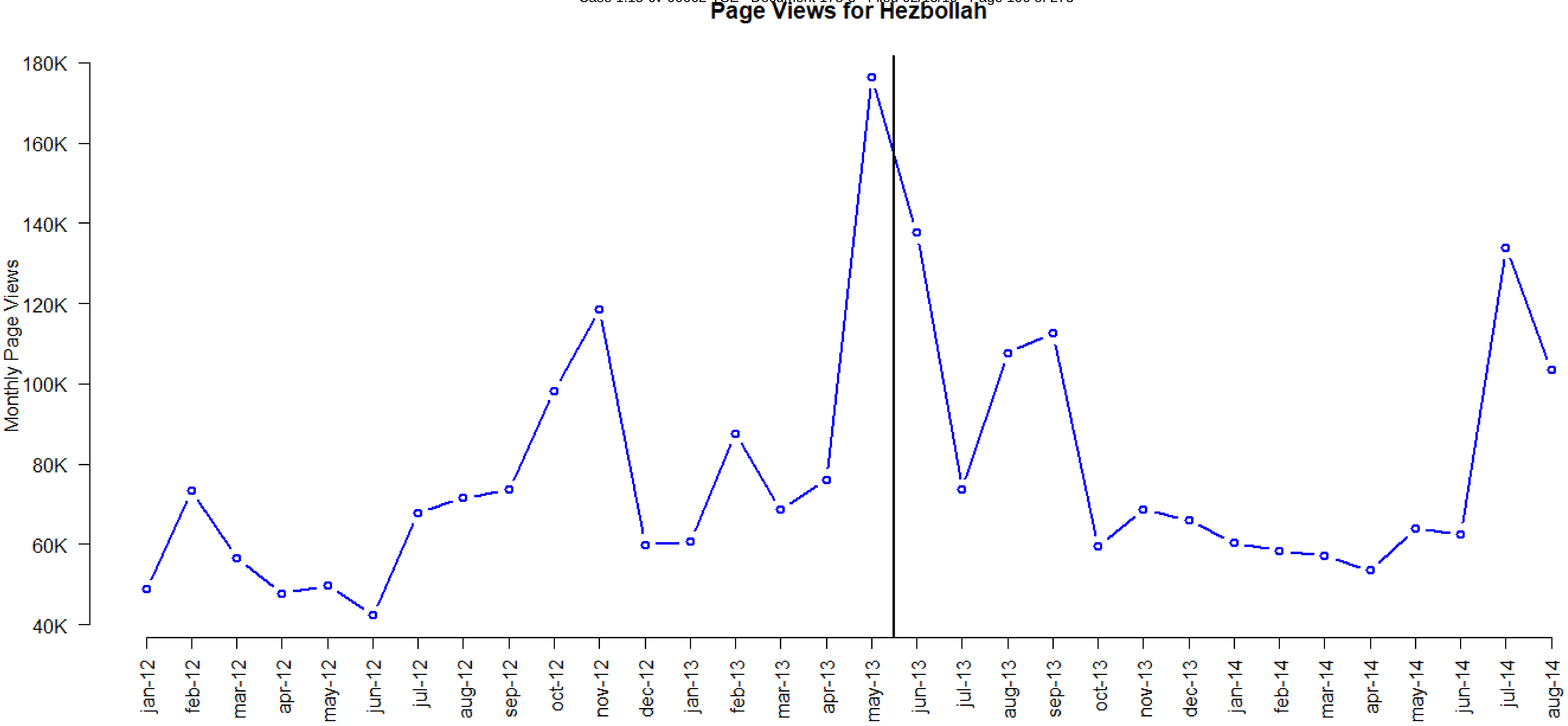
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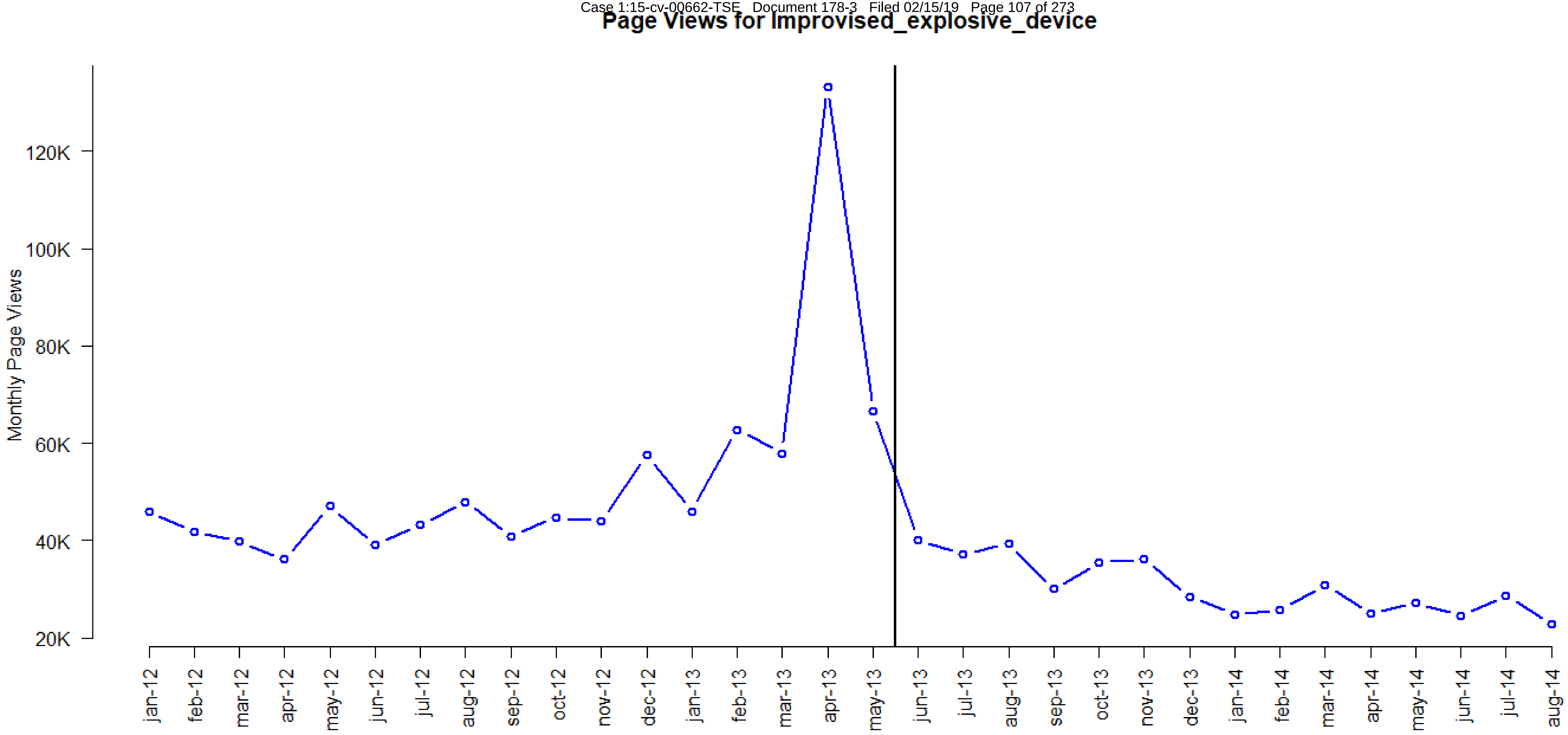
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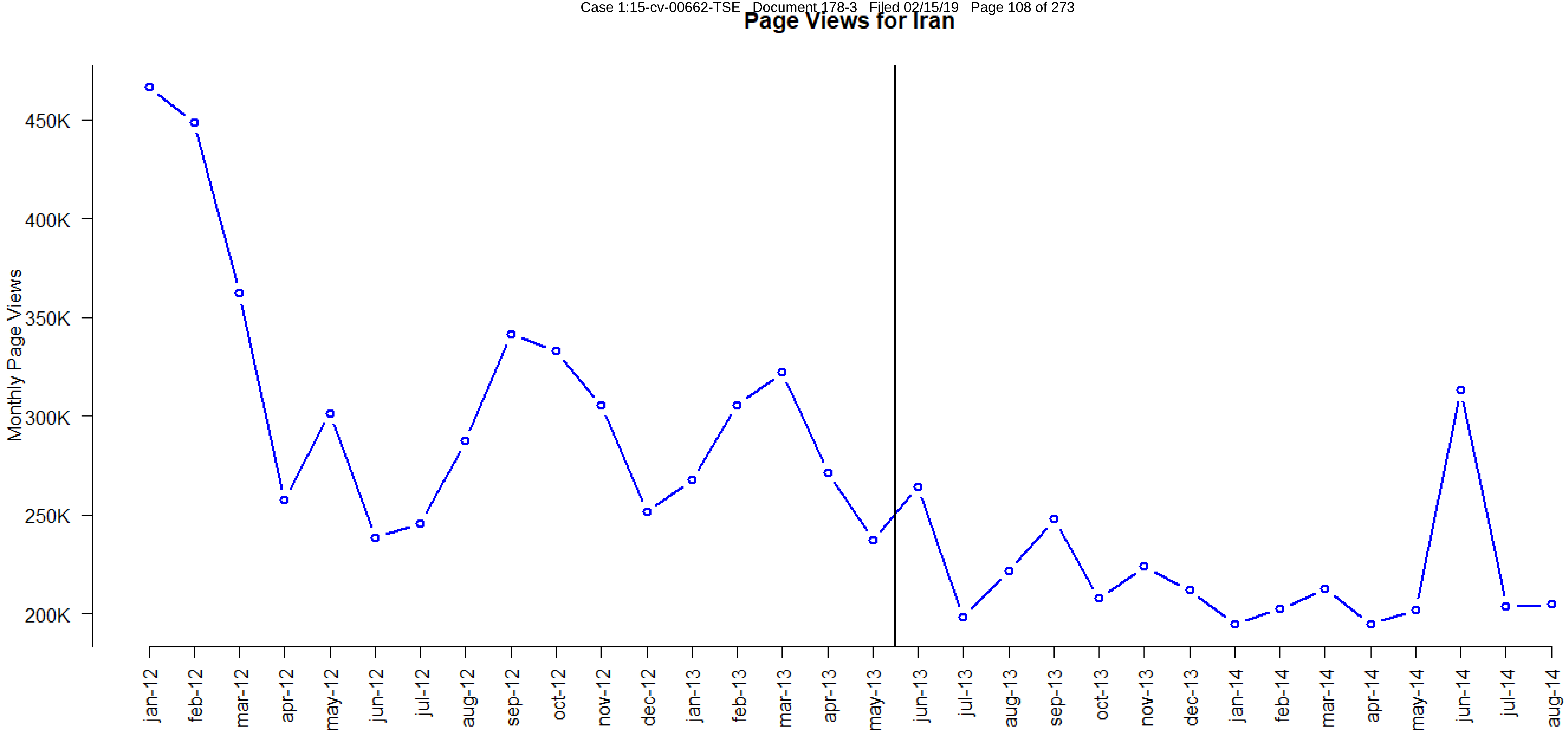
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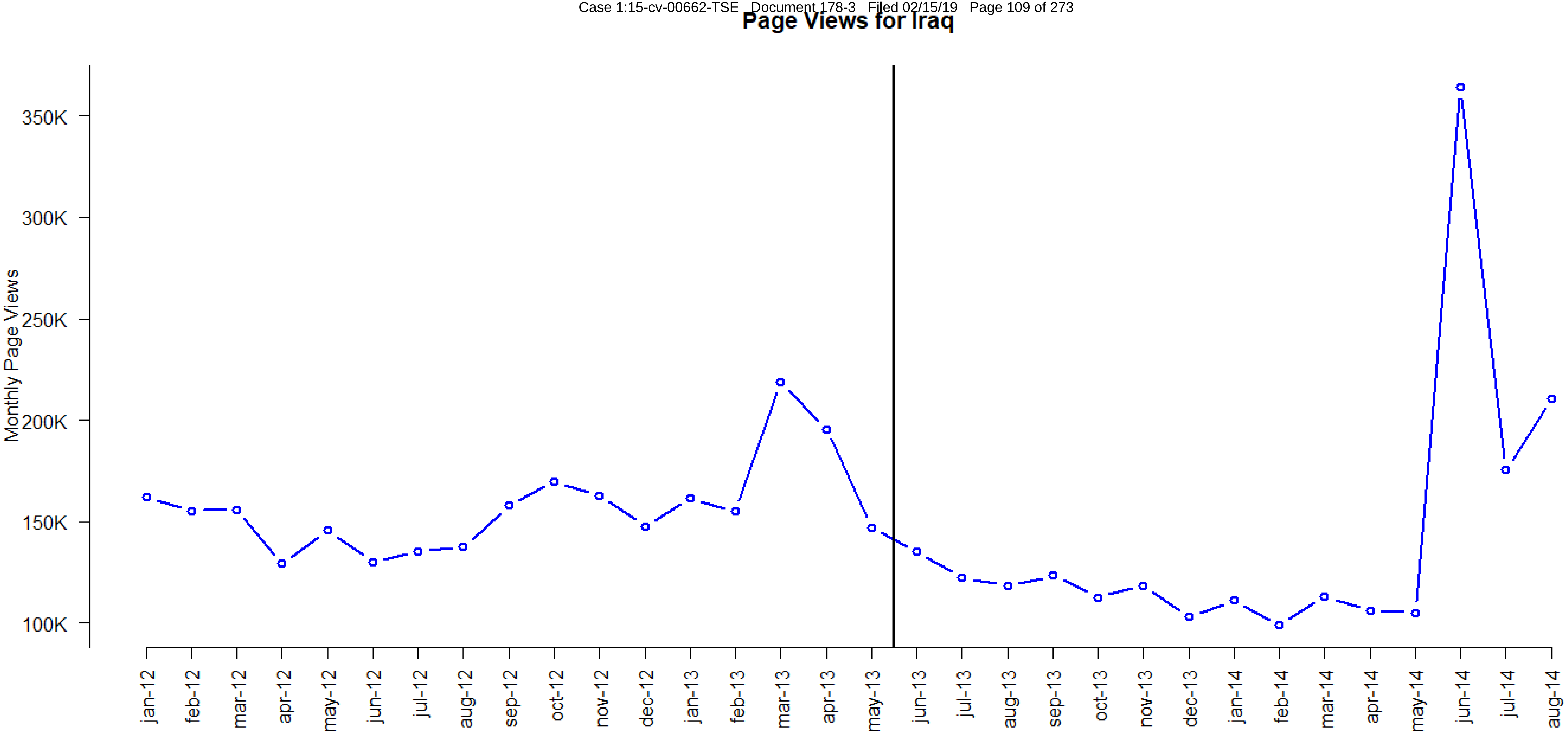
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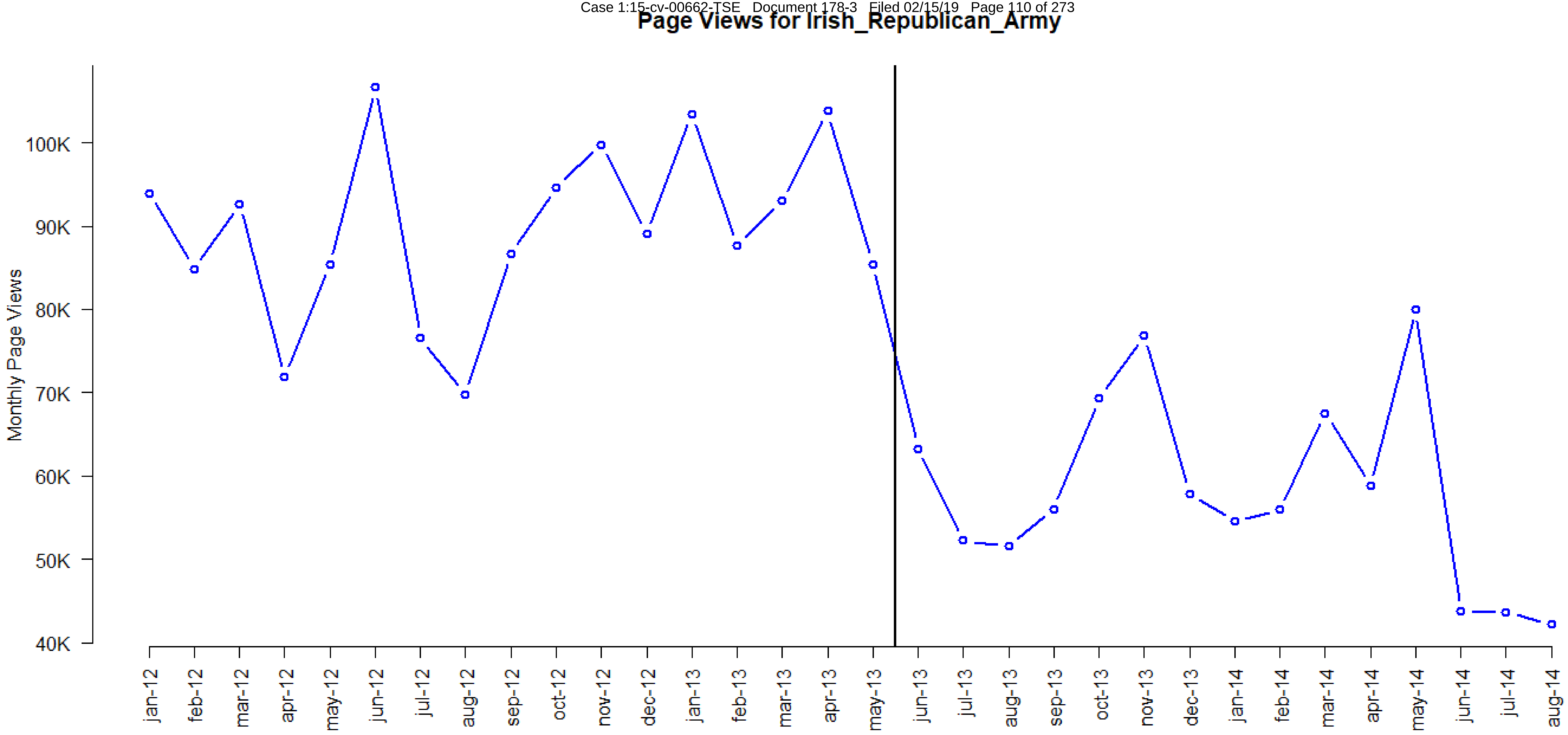
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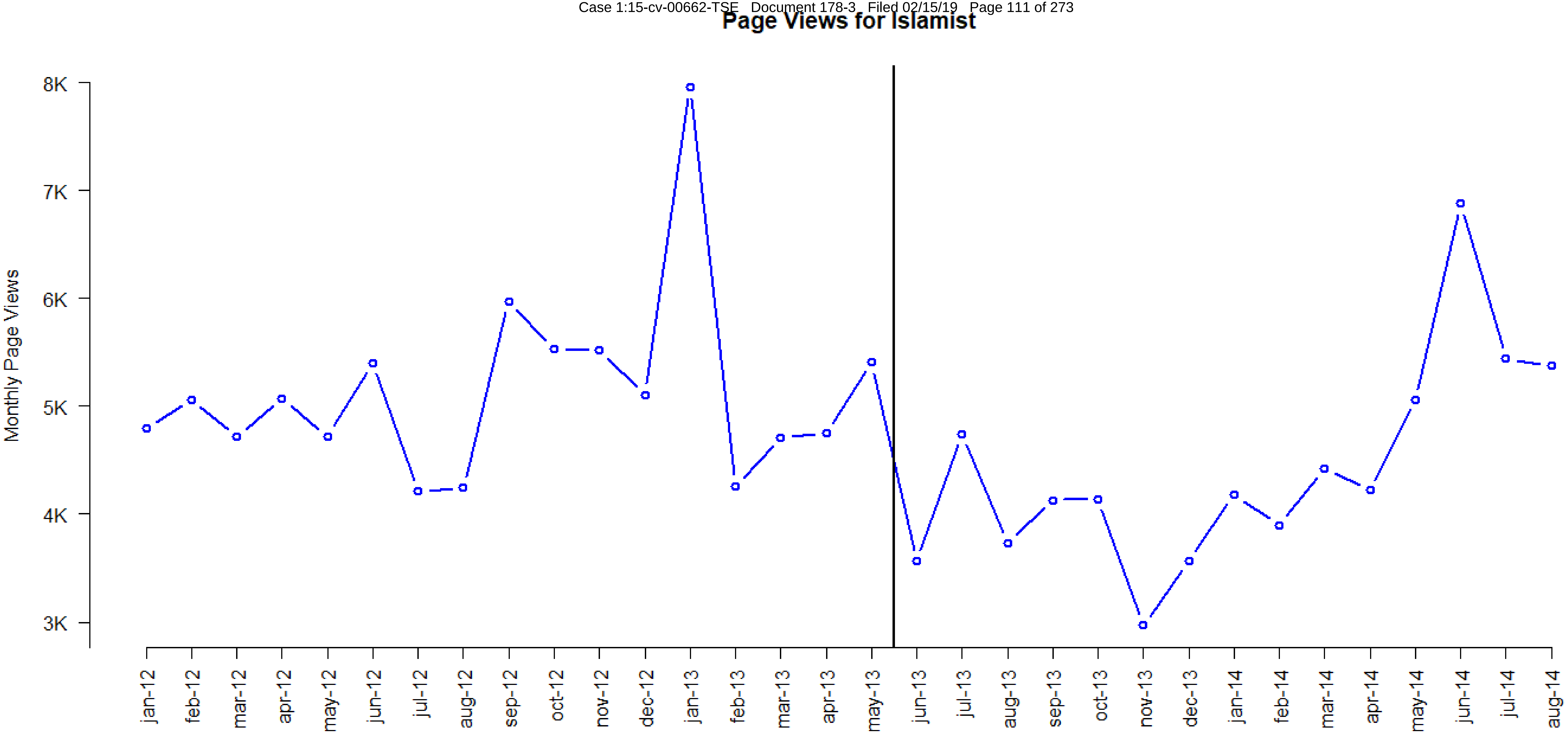
Page Views for Islamist
Monthly Page Views
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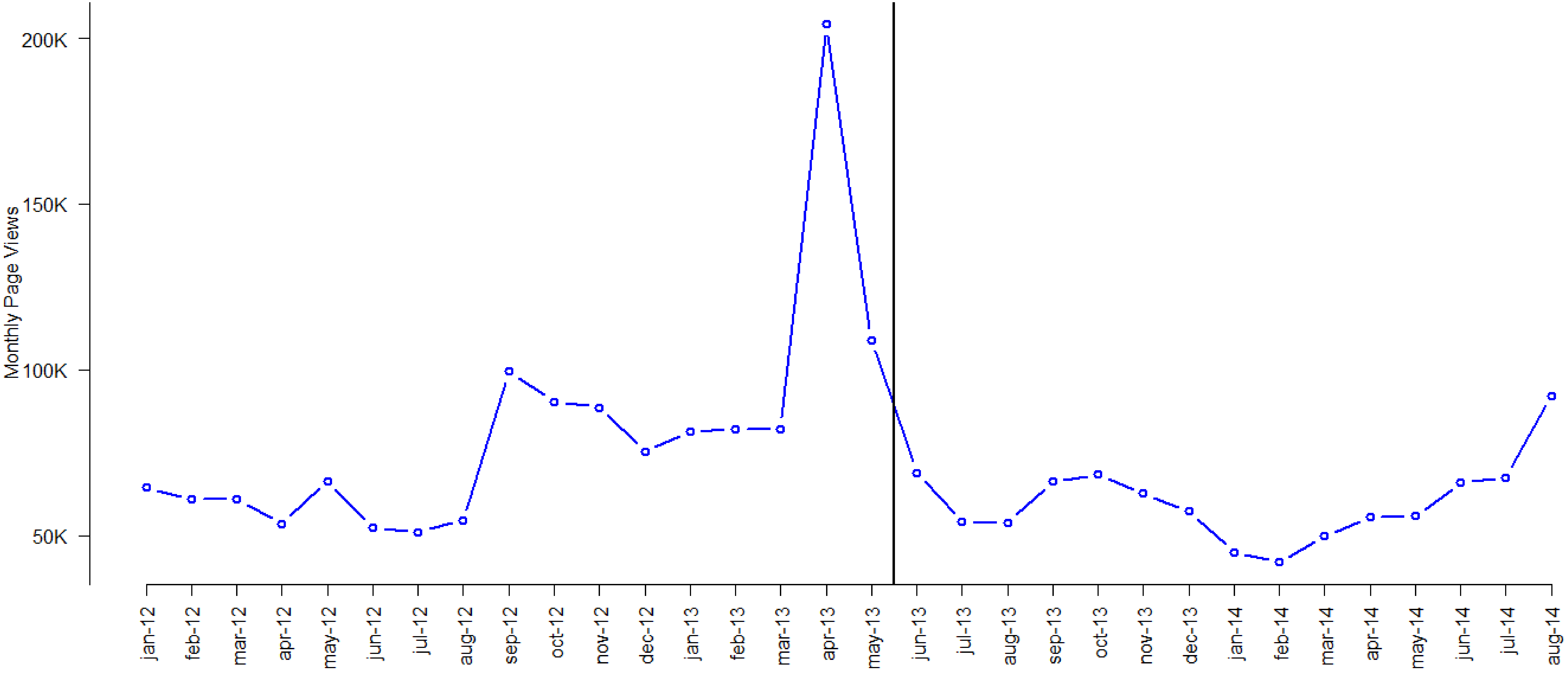
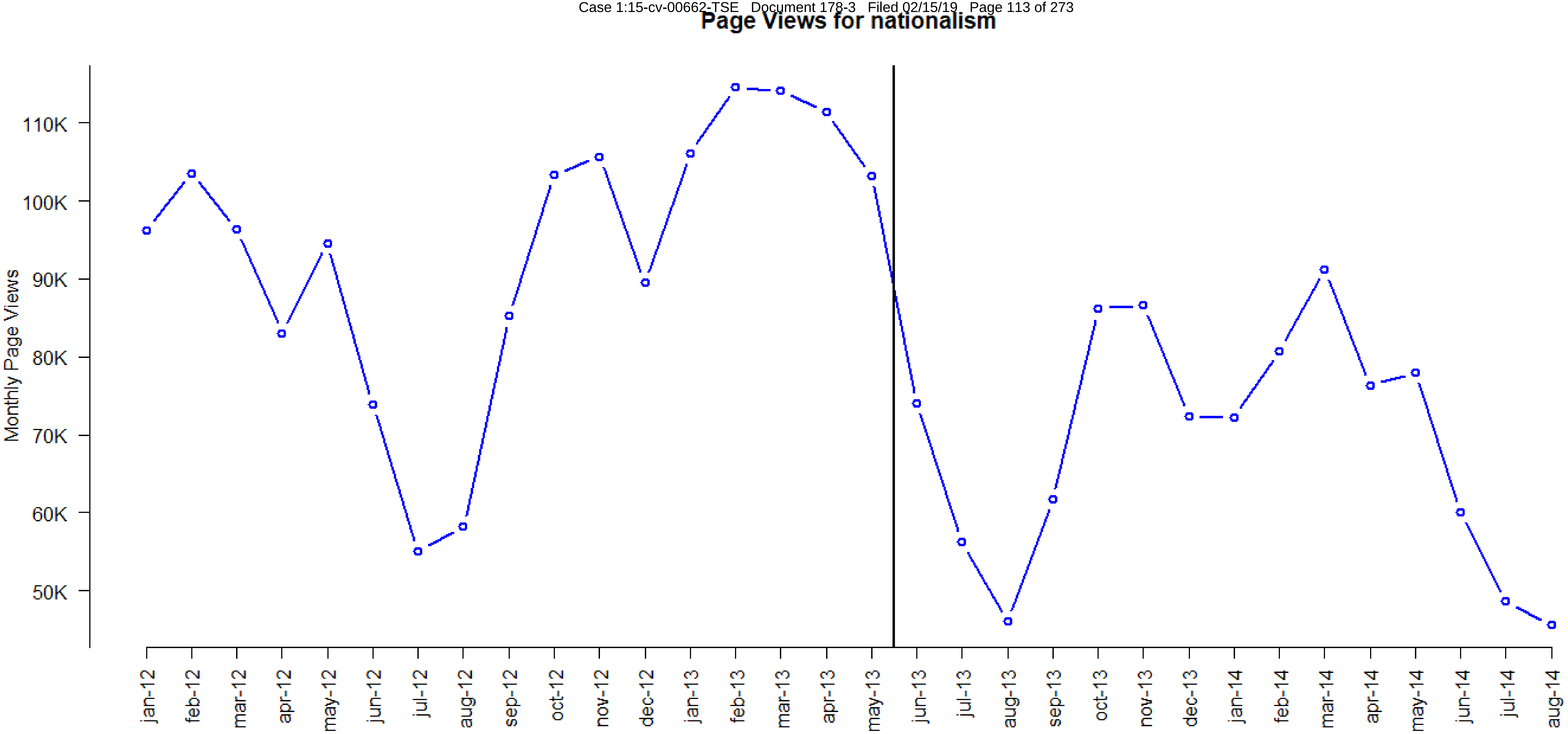
aug-14

## Page Views for Jihad




Page Views for nationalism
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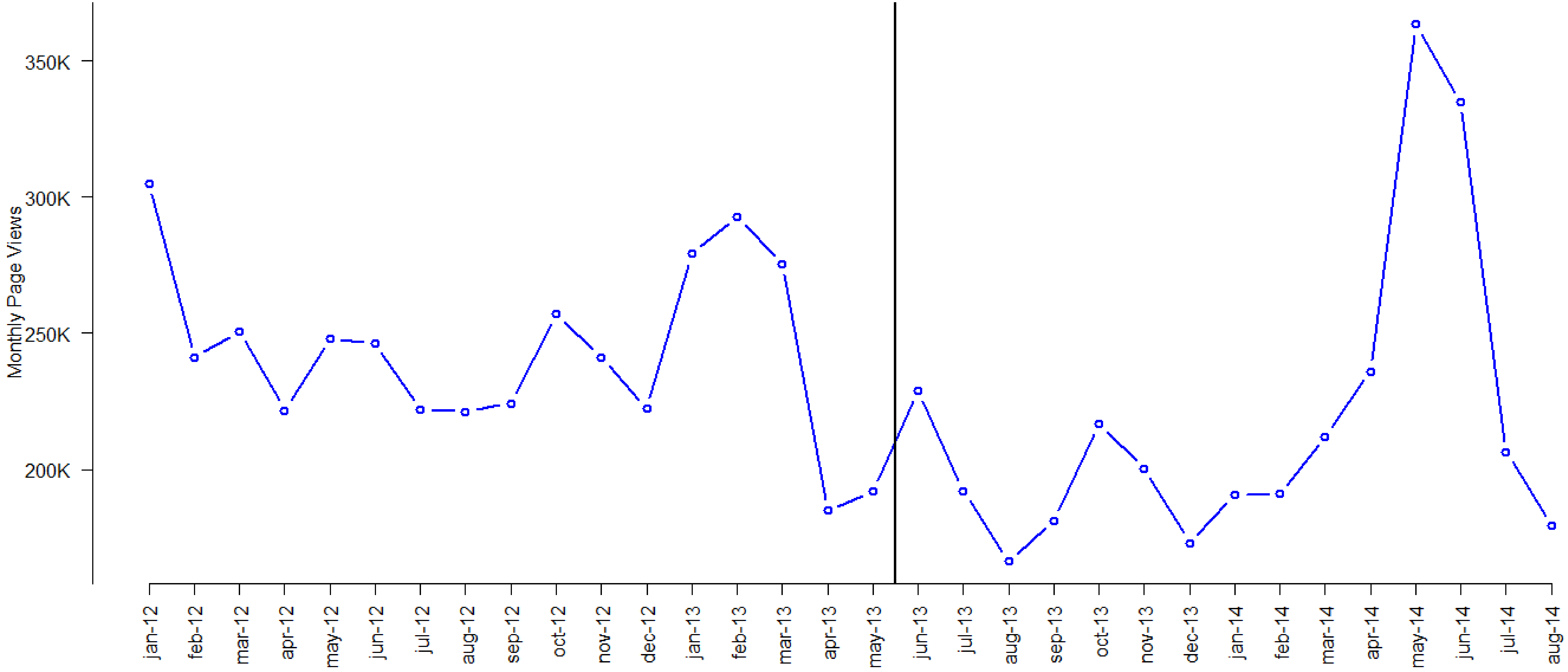
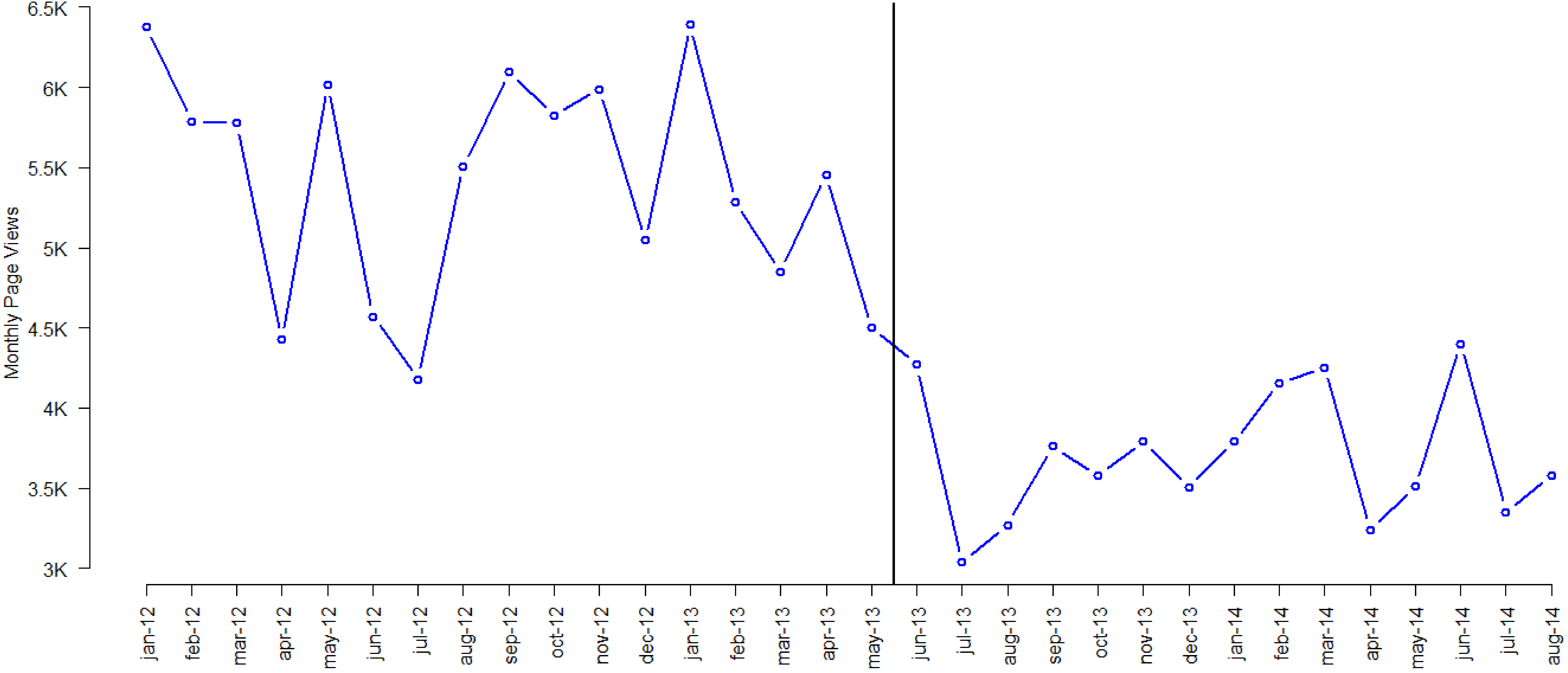
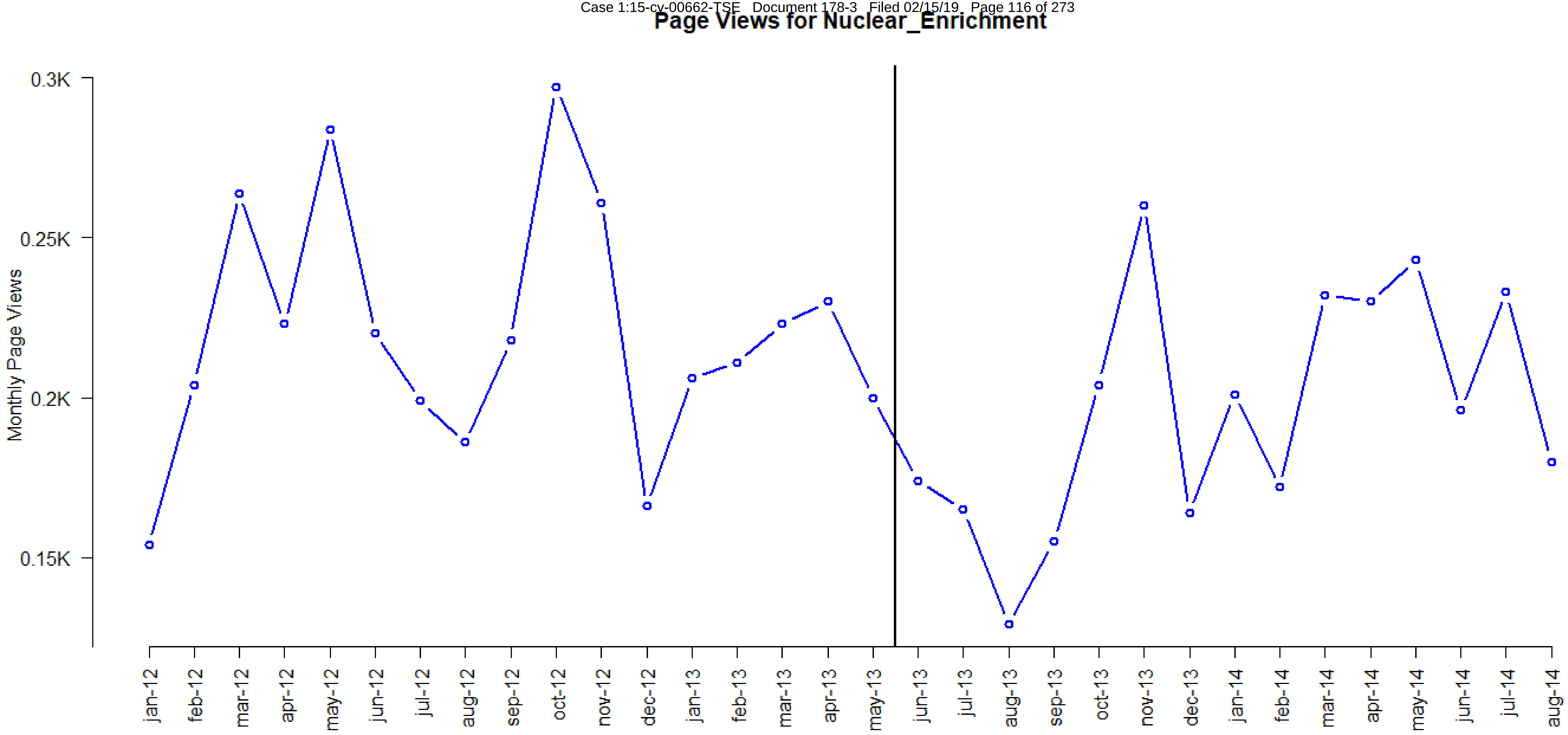
jul-14
aug-14

## Page Views for Nigeria



## Page Views for Nuclear




Page Views for Nuclear_Enrichment
Monthly Page Views
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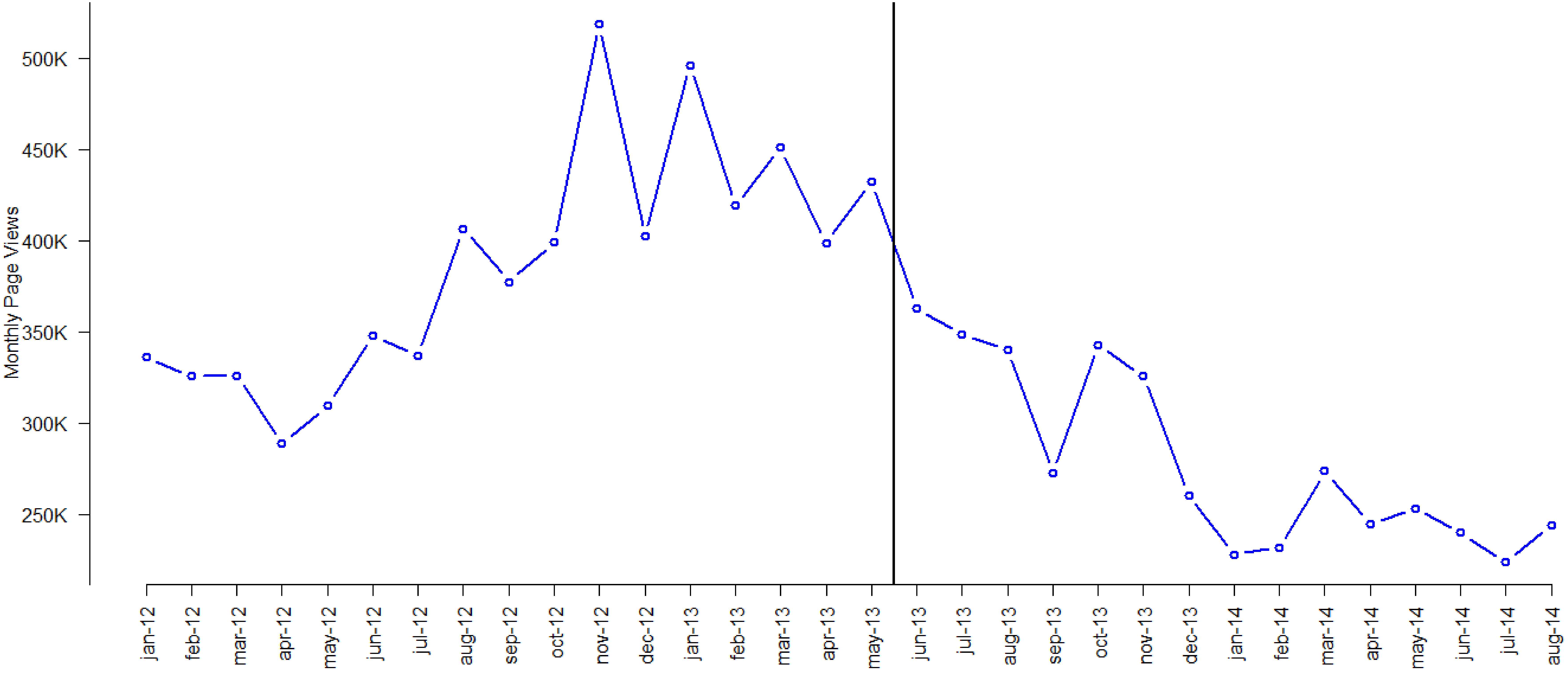
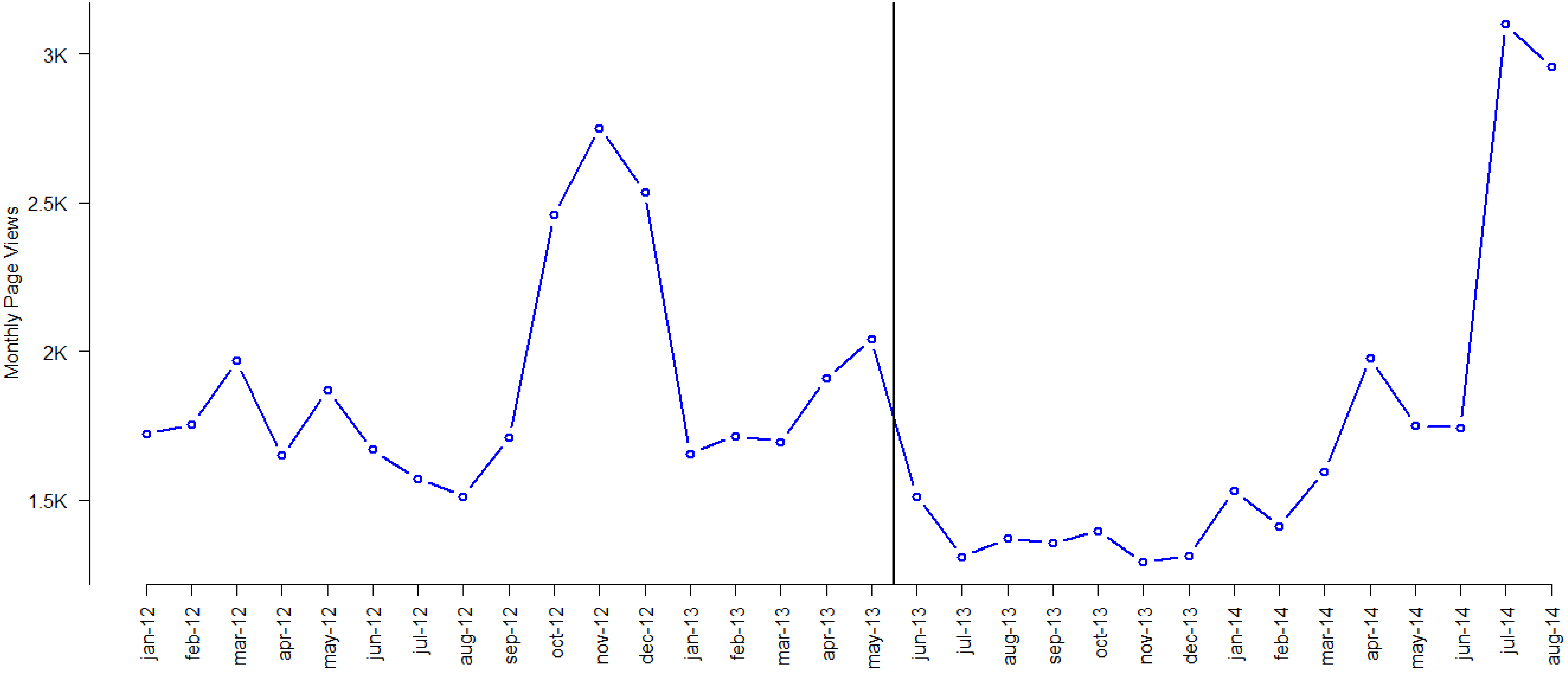
aug-14

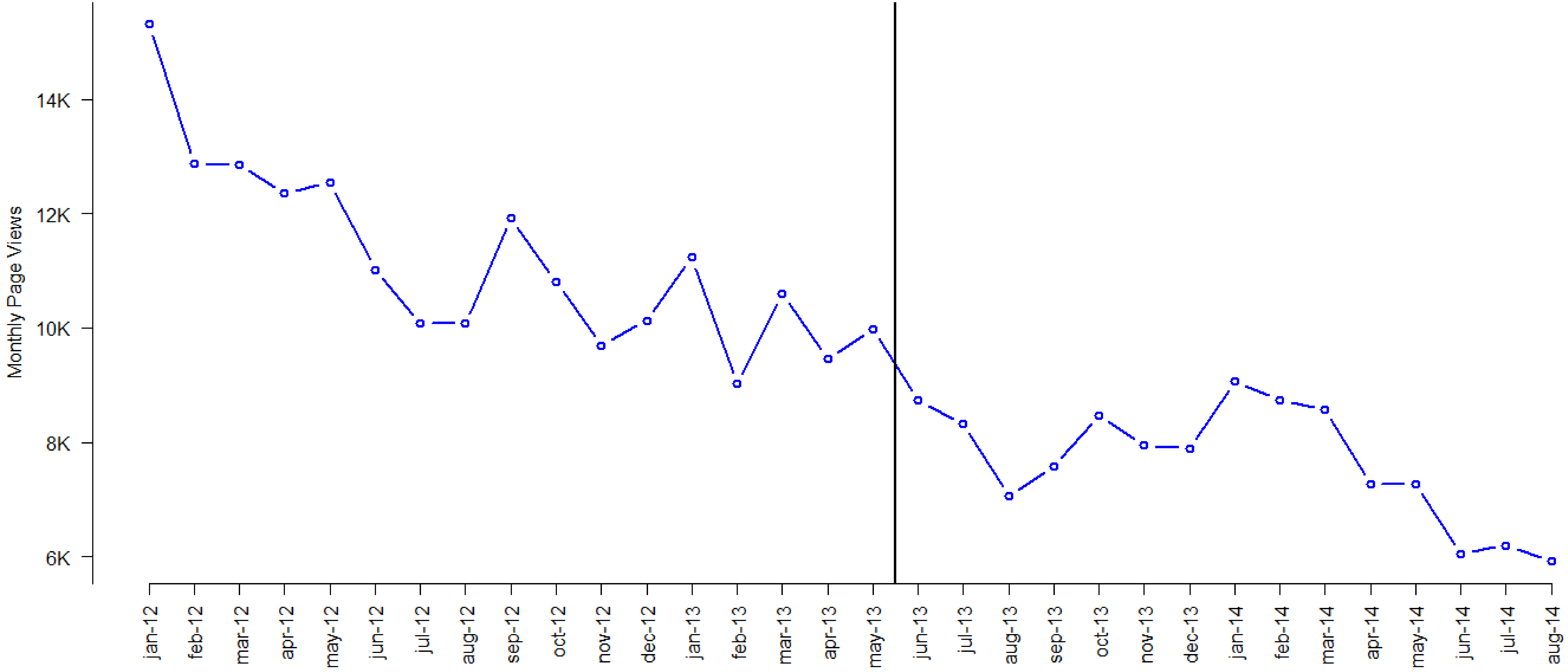
# Page Views for Pakistan

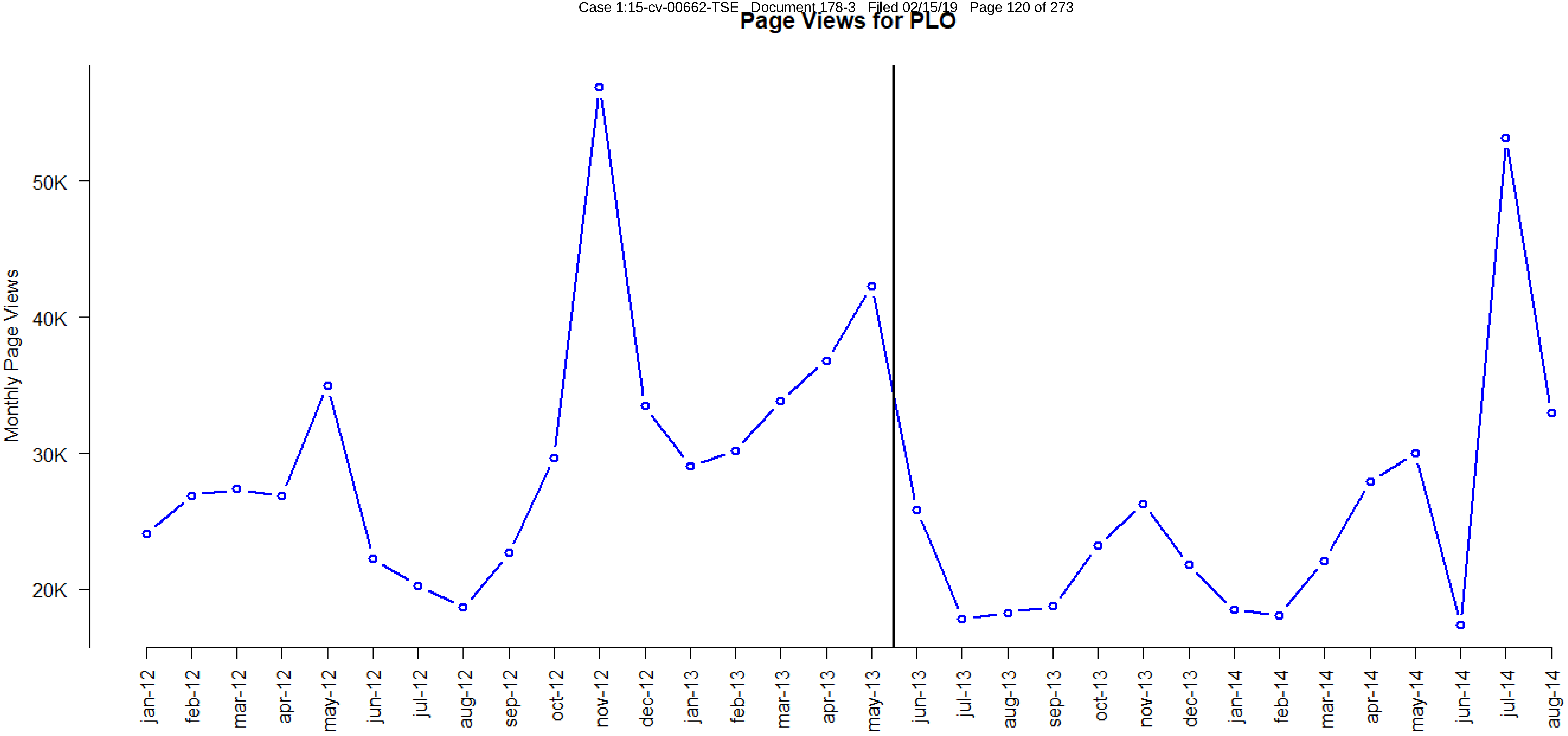


## Page Views for Palestine_Liberation_Fron



## Page Views for Pirates




Page Views for PLO
Monthly Page Views
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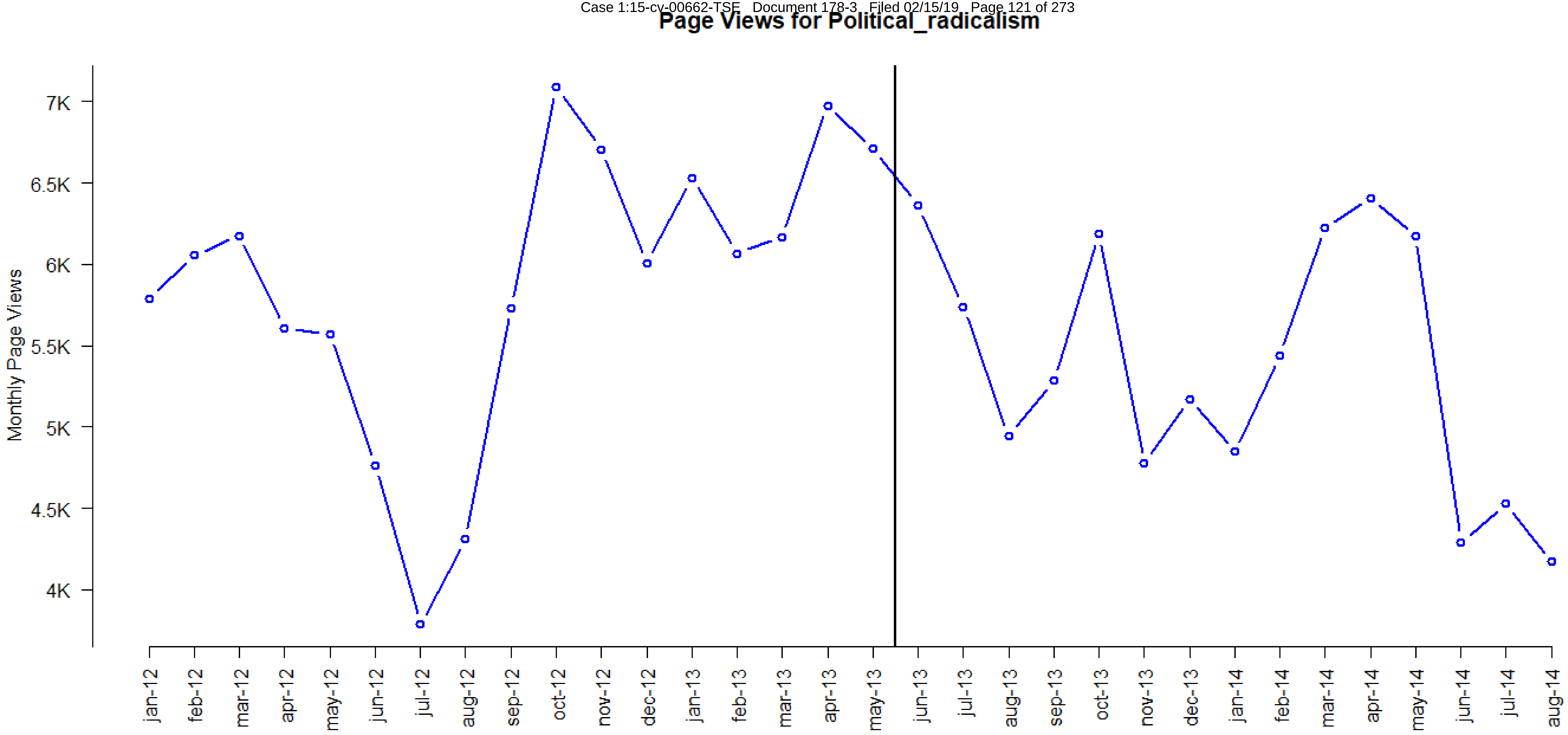
Page Views for Political_radicalism
Monthly Page Views
7K
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4.5K
4K
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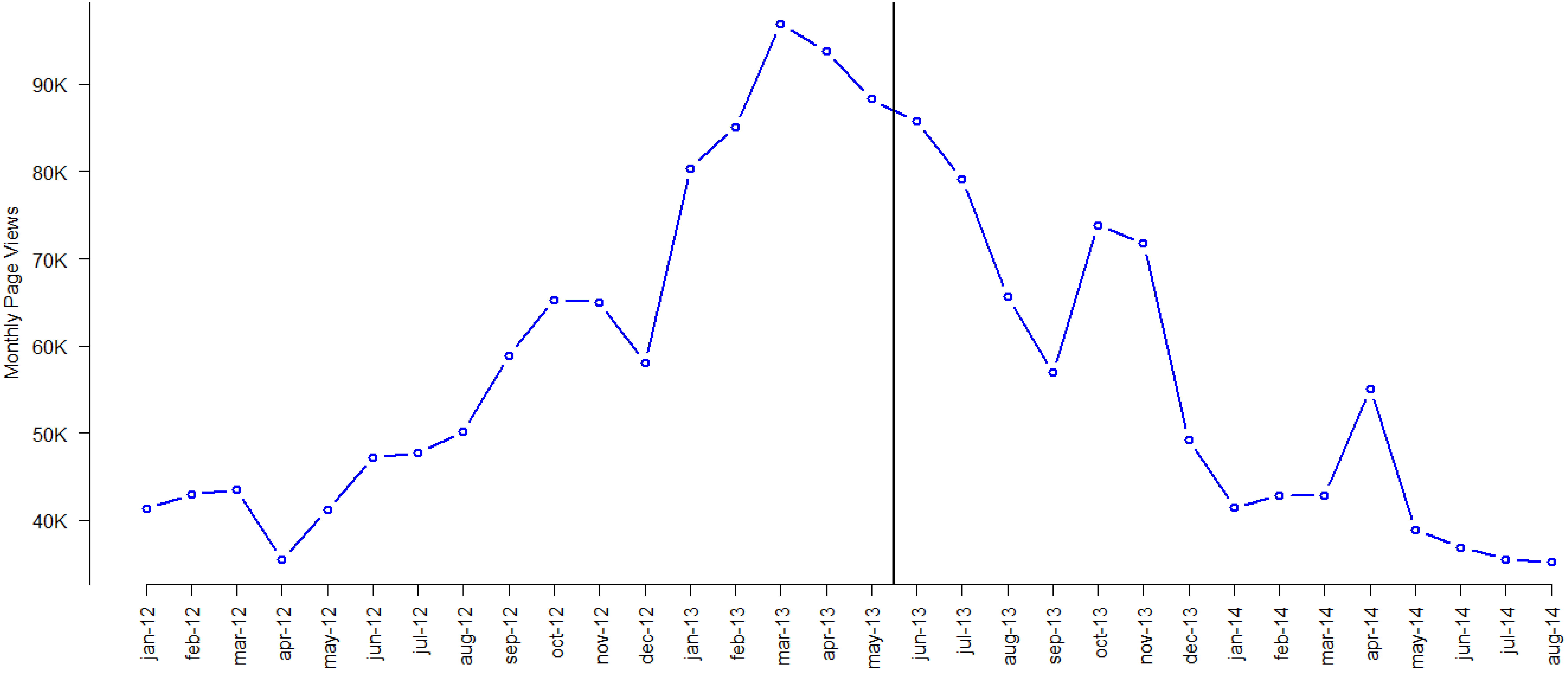
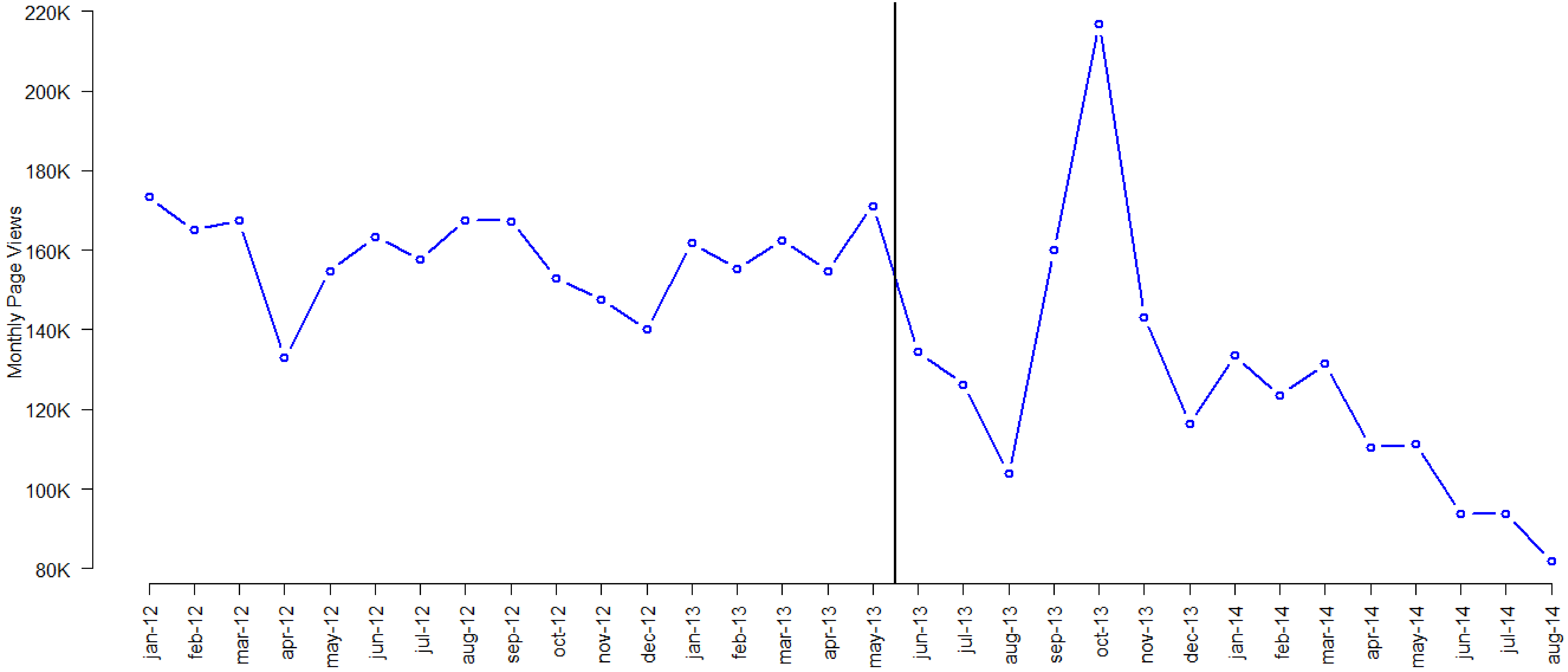
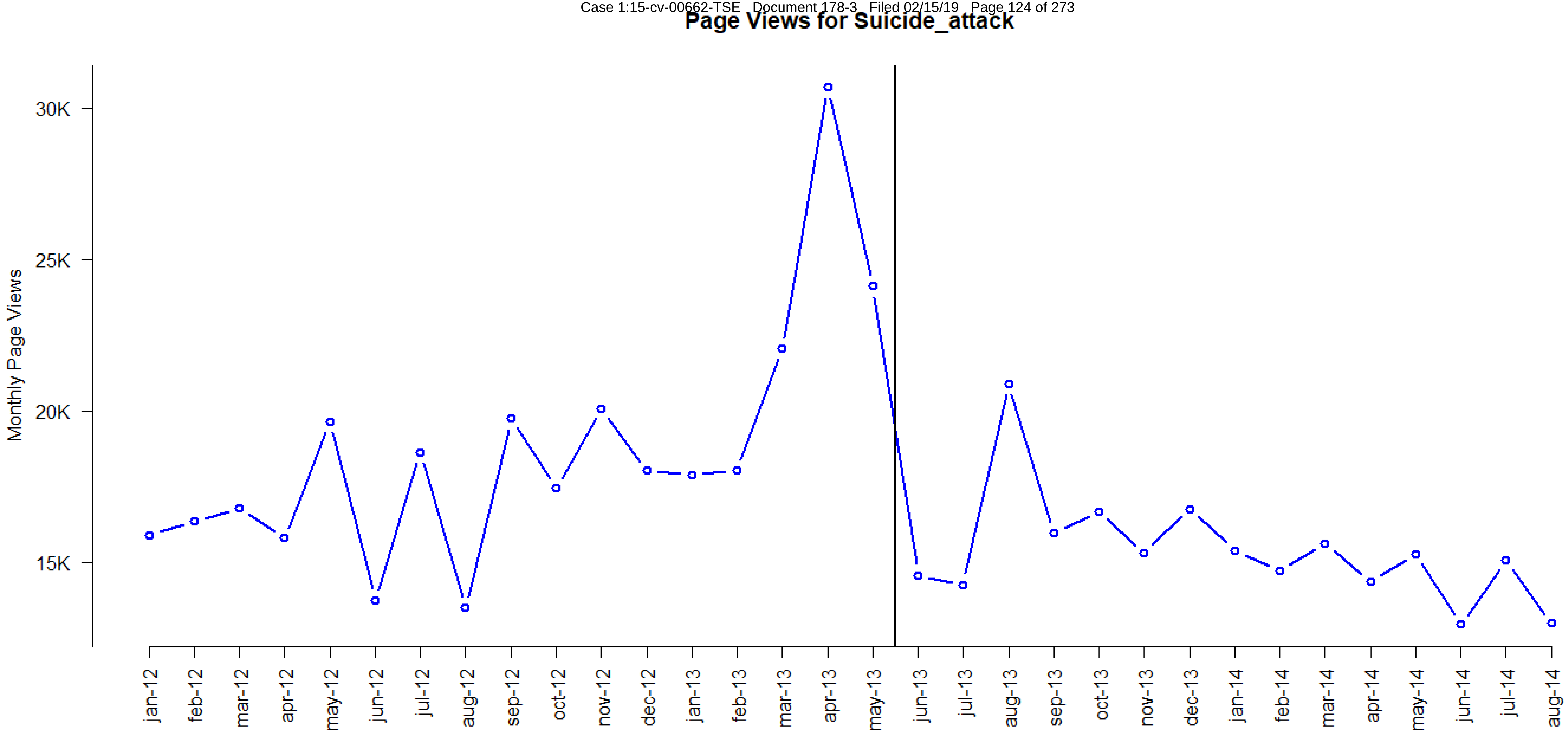
## Page Views for Recruitment



# Page Views for Somalia




Page Views for Suicide_attack
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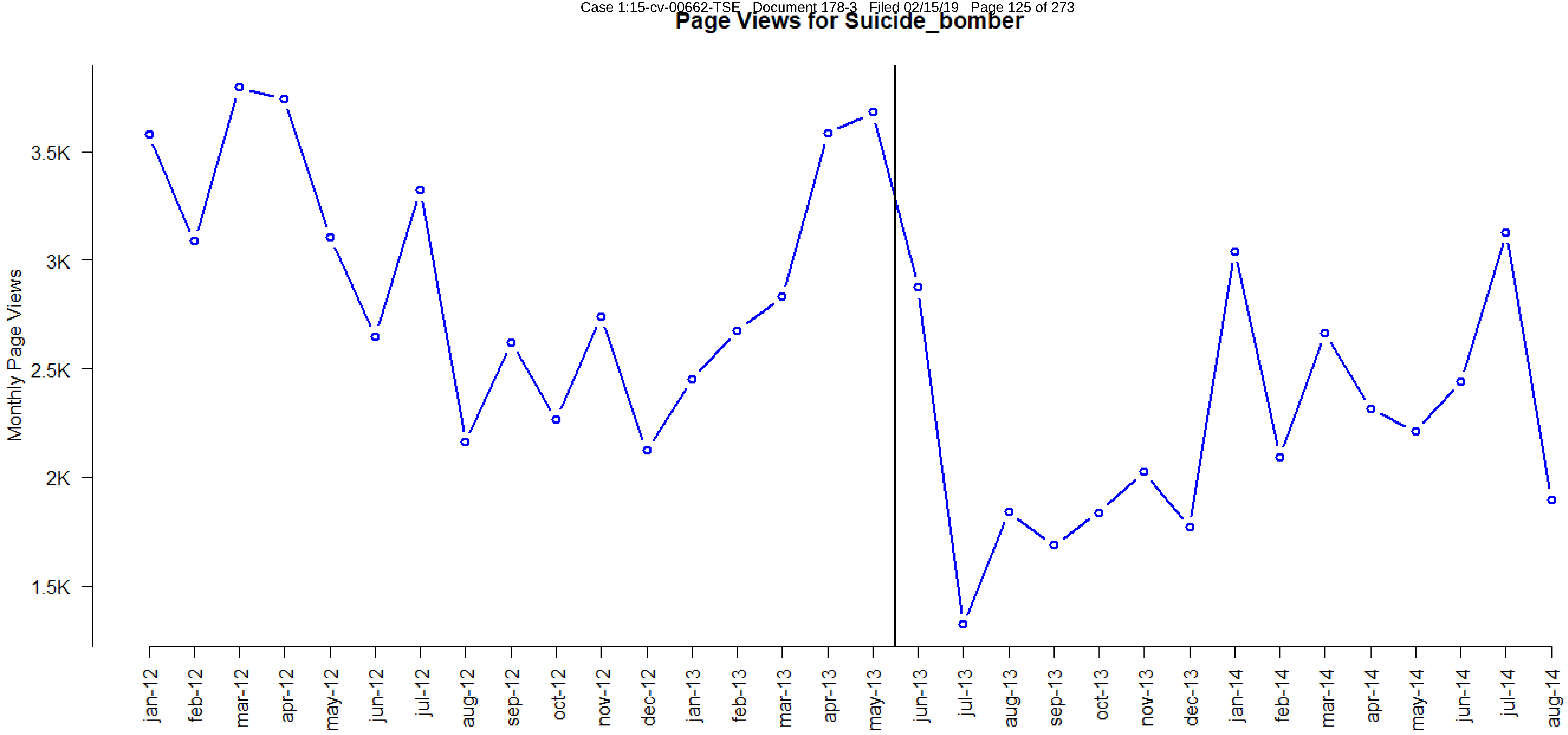
Page Views for Suicide_bomber
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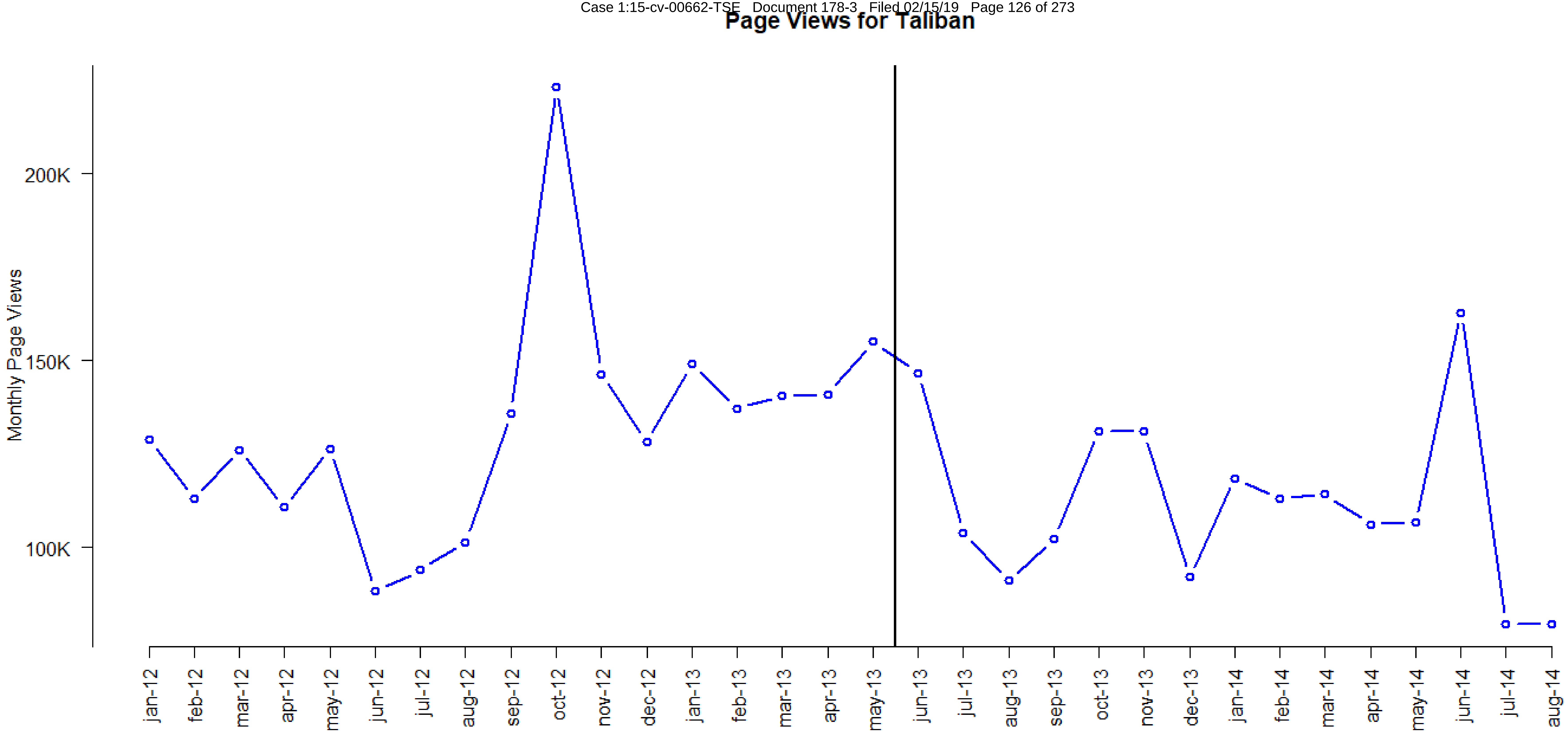
Page Views for Taliban
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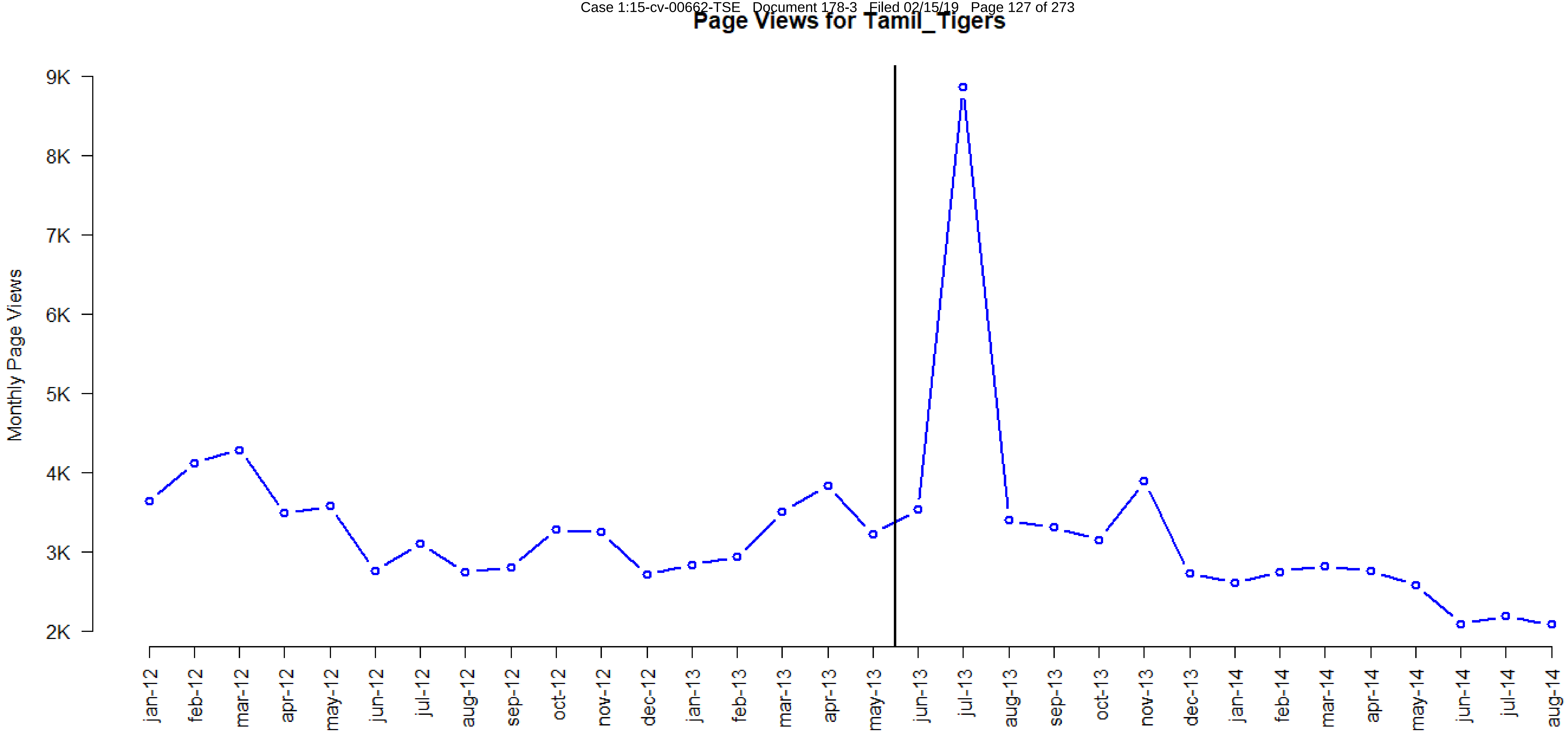
Page Views for Tamil_Tigers
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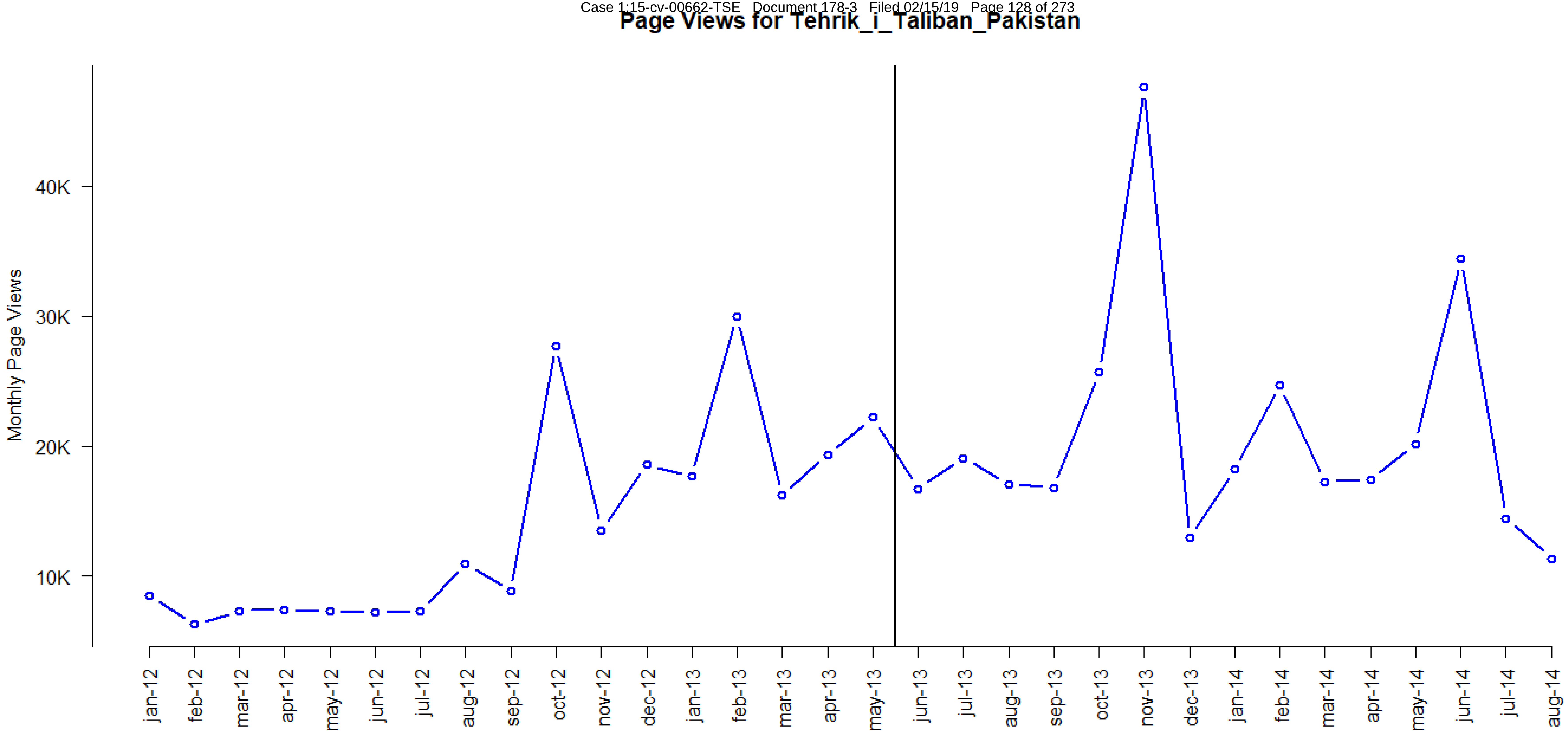
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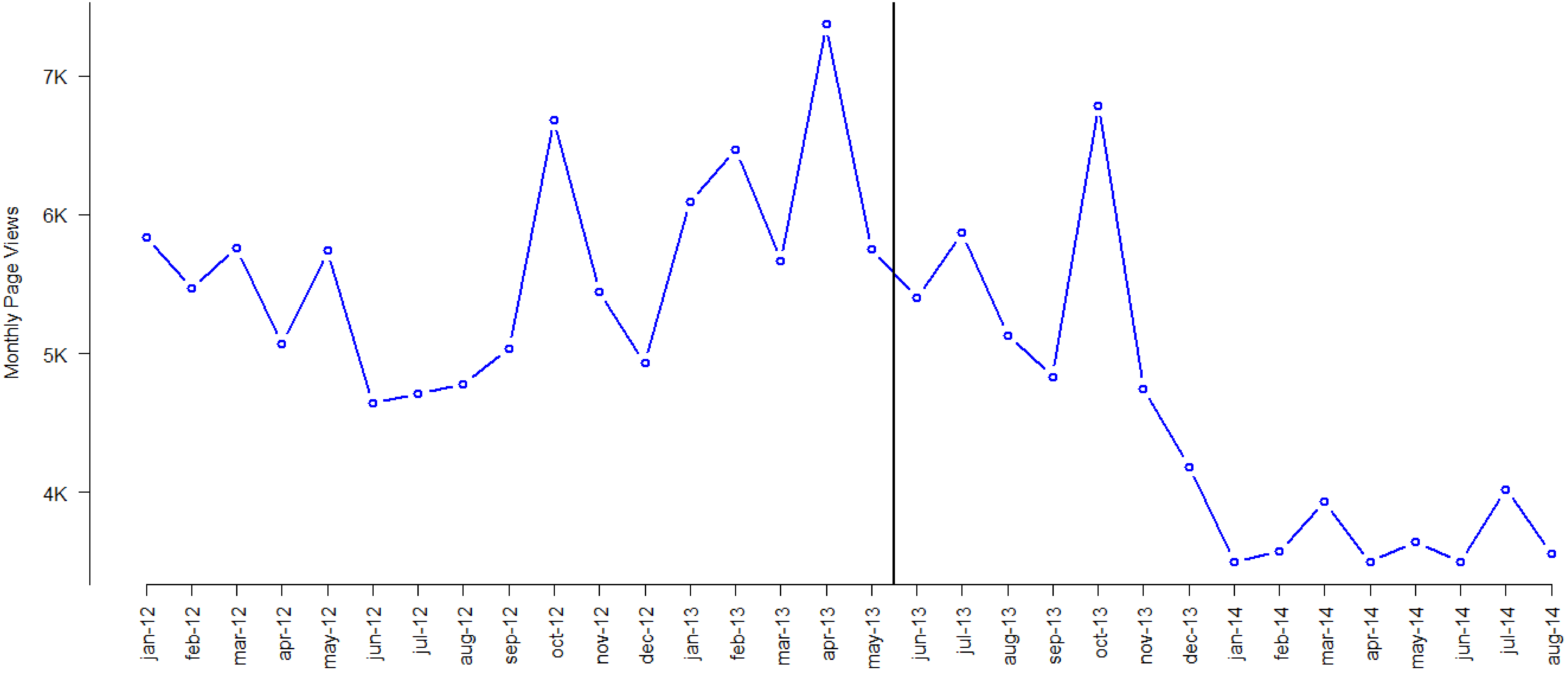
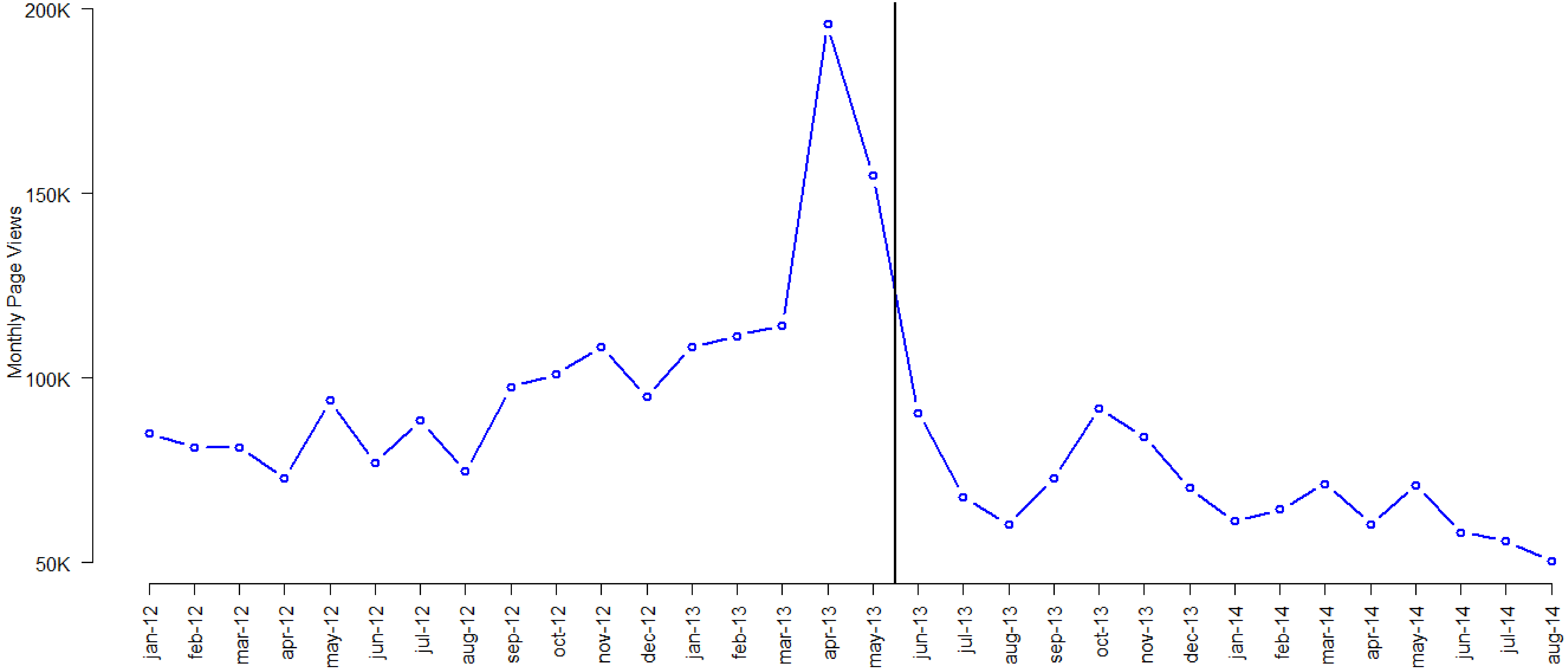
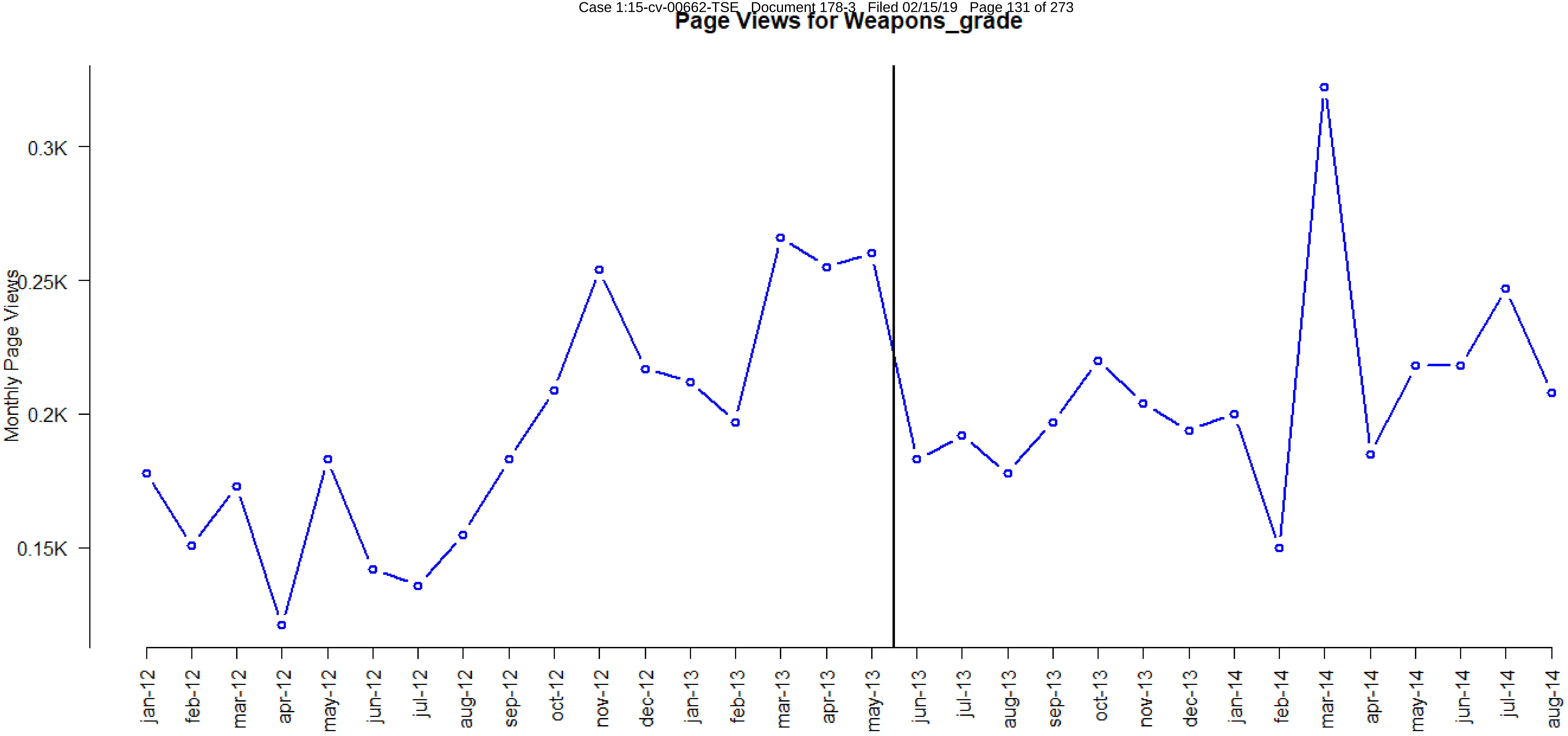
aug-14

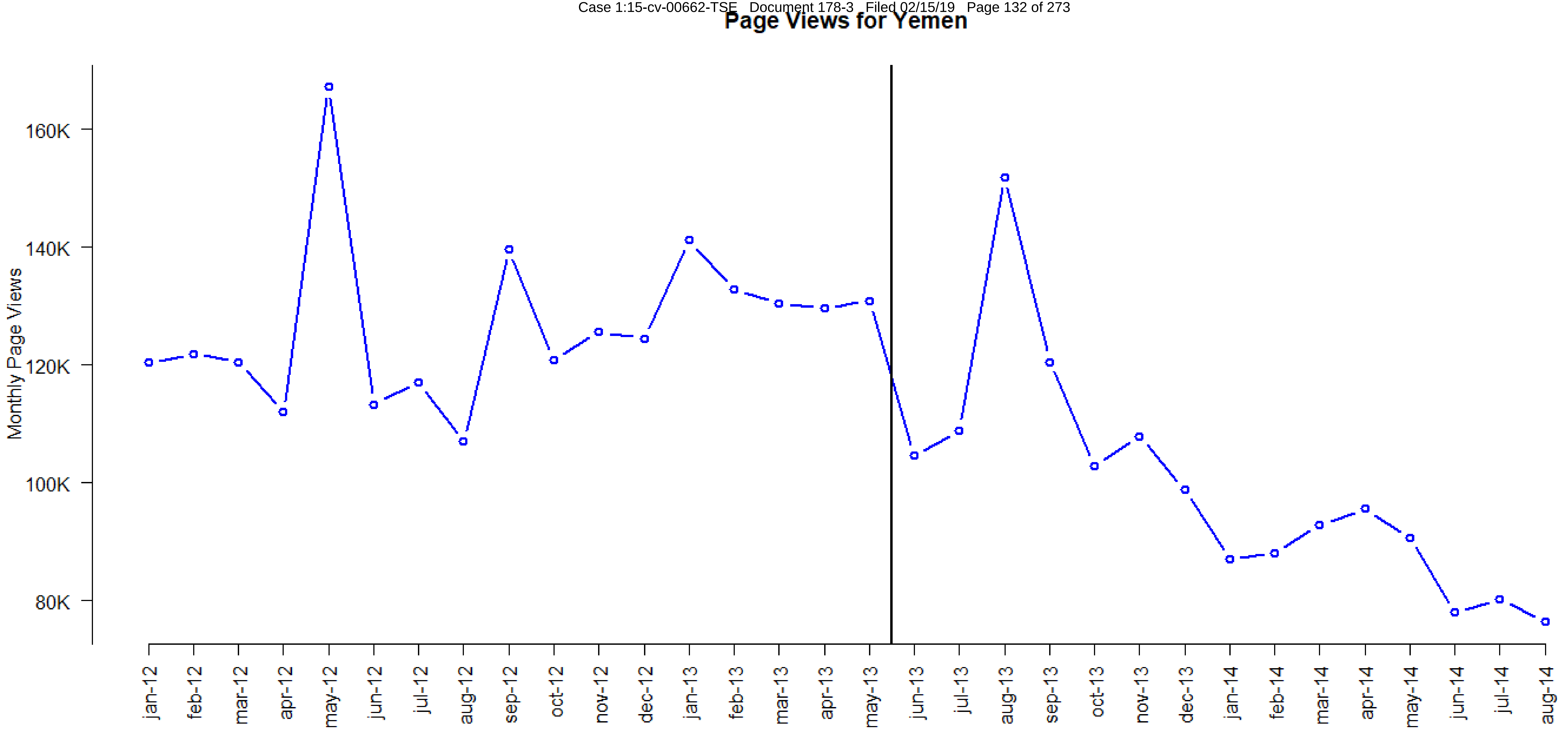
## Page Views for terror



## Page Views for terrorism

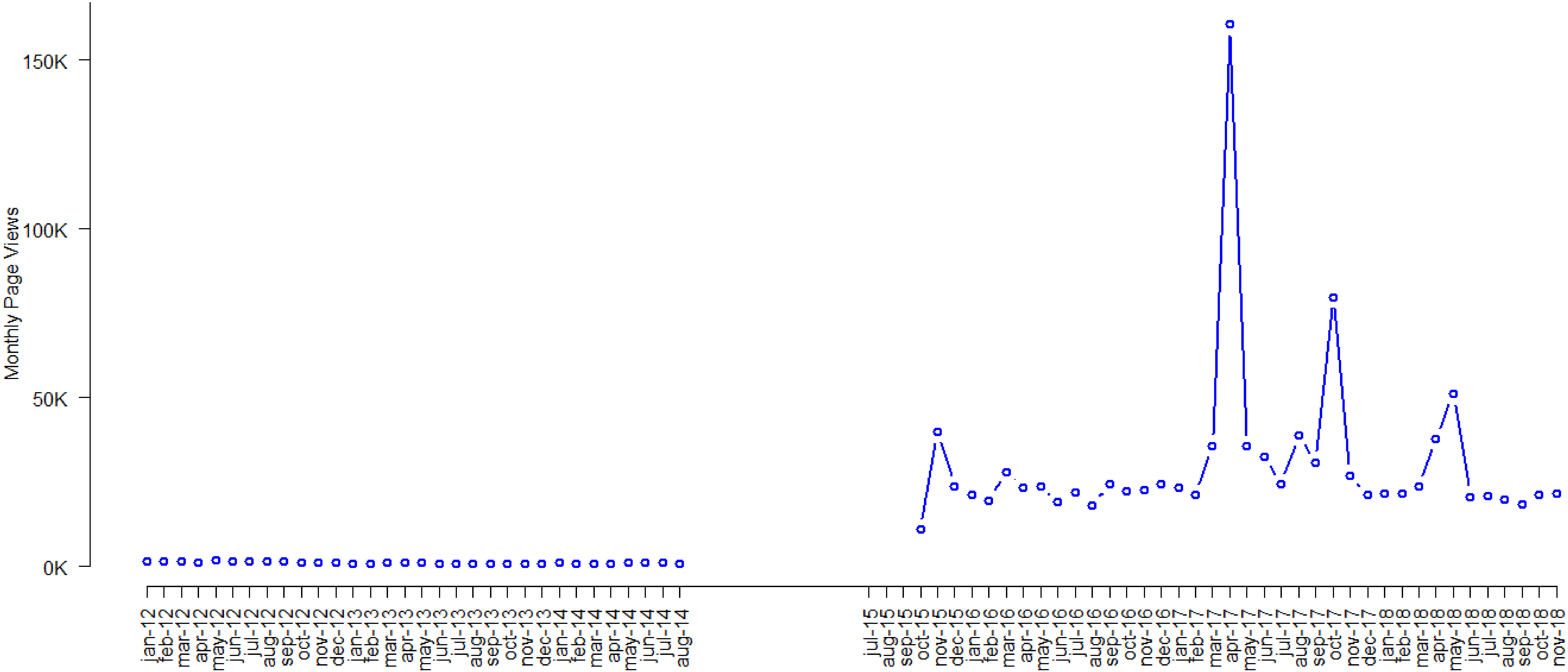


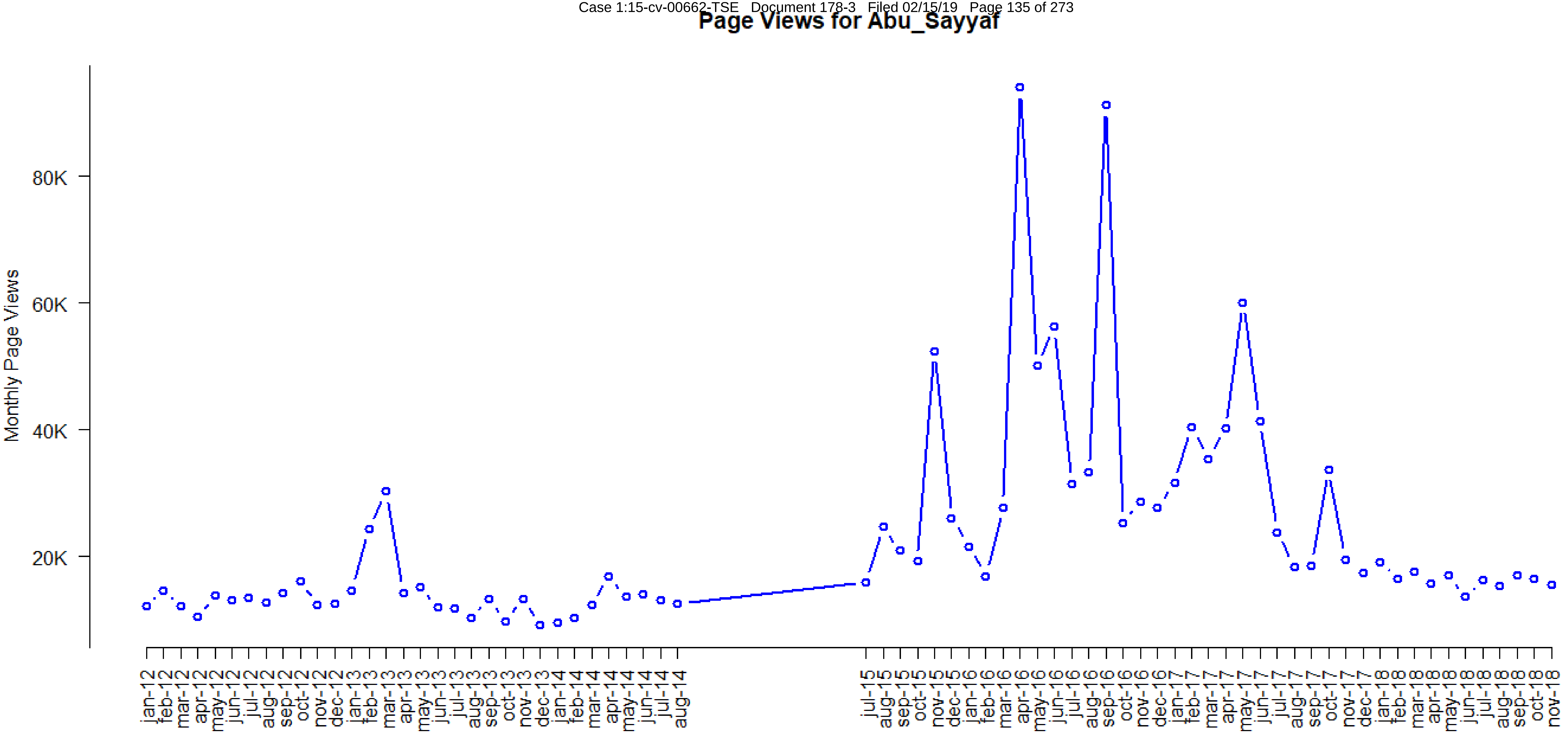

Page Views for Weapons_grade
Monthly Page Views
0.3K
0.25K
0.2K
0.15K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14


Page Views for Yemen
Monthly Page Views
160K
140K
120K
100K
80K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

# APPENDIX V: Page Views for 48 Terror Articles, Extended Time Period

# Page Views for _Euskadi_ta_Askatasuna




Page Views for Abu_Sayyaf
Monthly Page Views
80K
60K
40K
20K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14
jul-15
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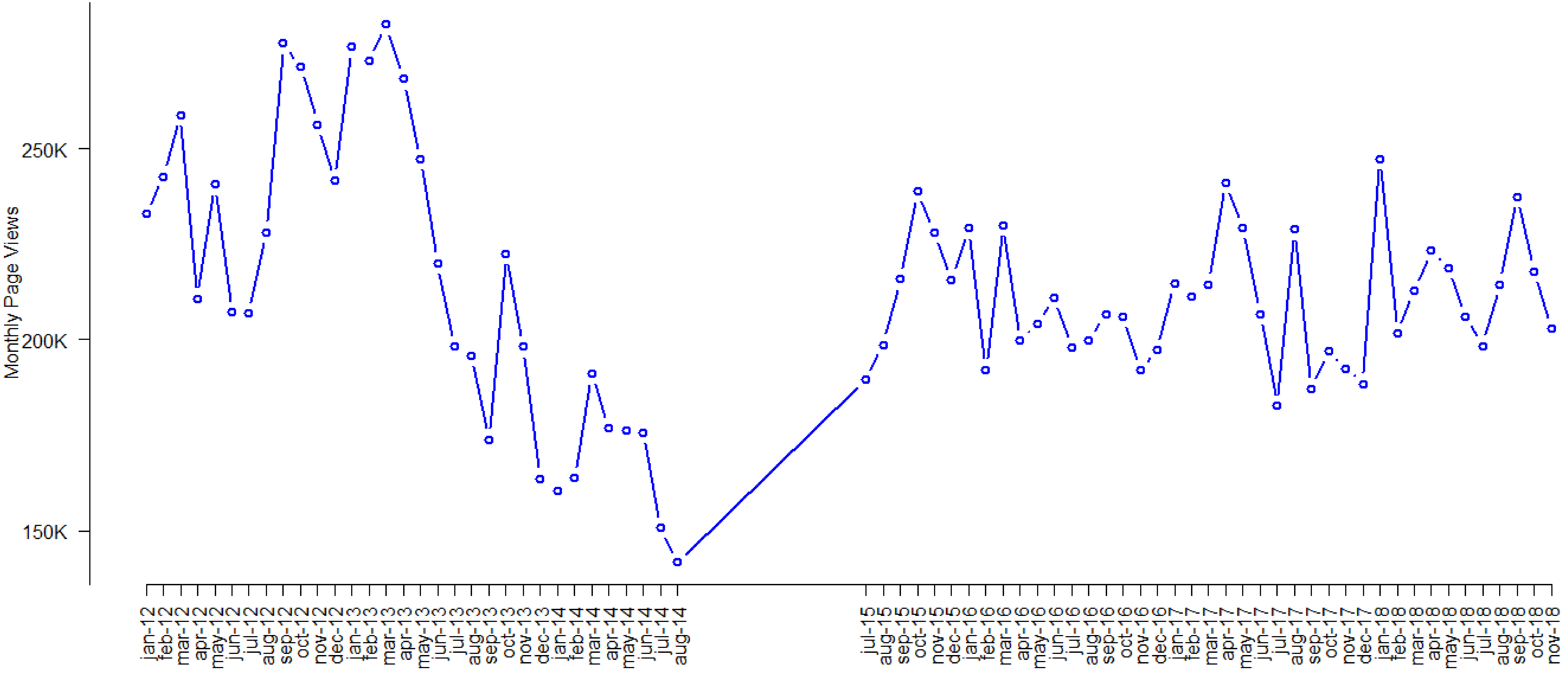
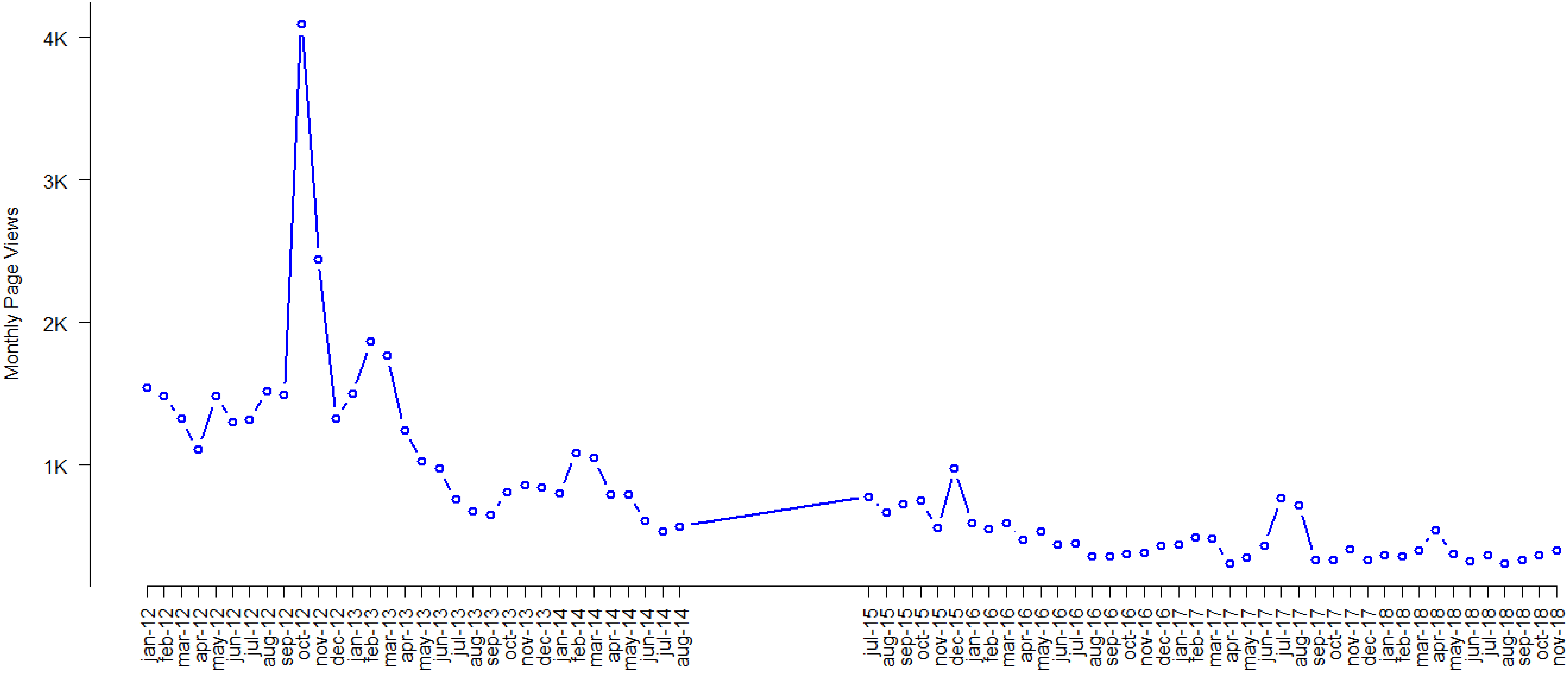
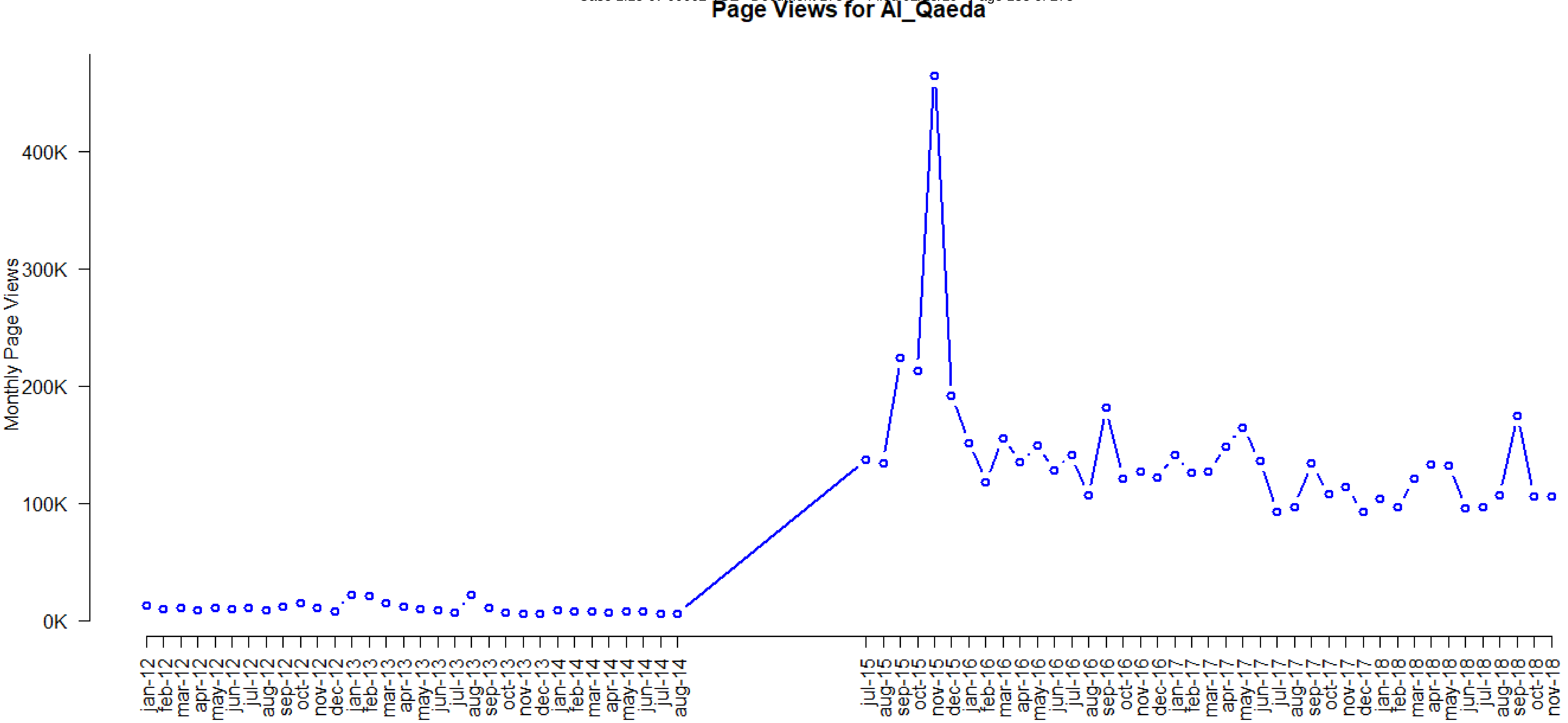
apr-16
may-16
jun-16
jul-16
aug-16
sep-16
oct-16
nov-16
dec-16
jan-17
feb-17
mar-17
apr-17
may-17
jun-17
jul-17
aug-17
sep-17
oct-17
nov-17
dec-17
jan-18
feb-18
mar-18
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18

# Page Views for Afghanistan

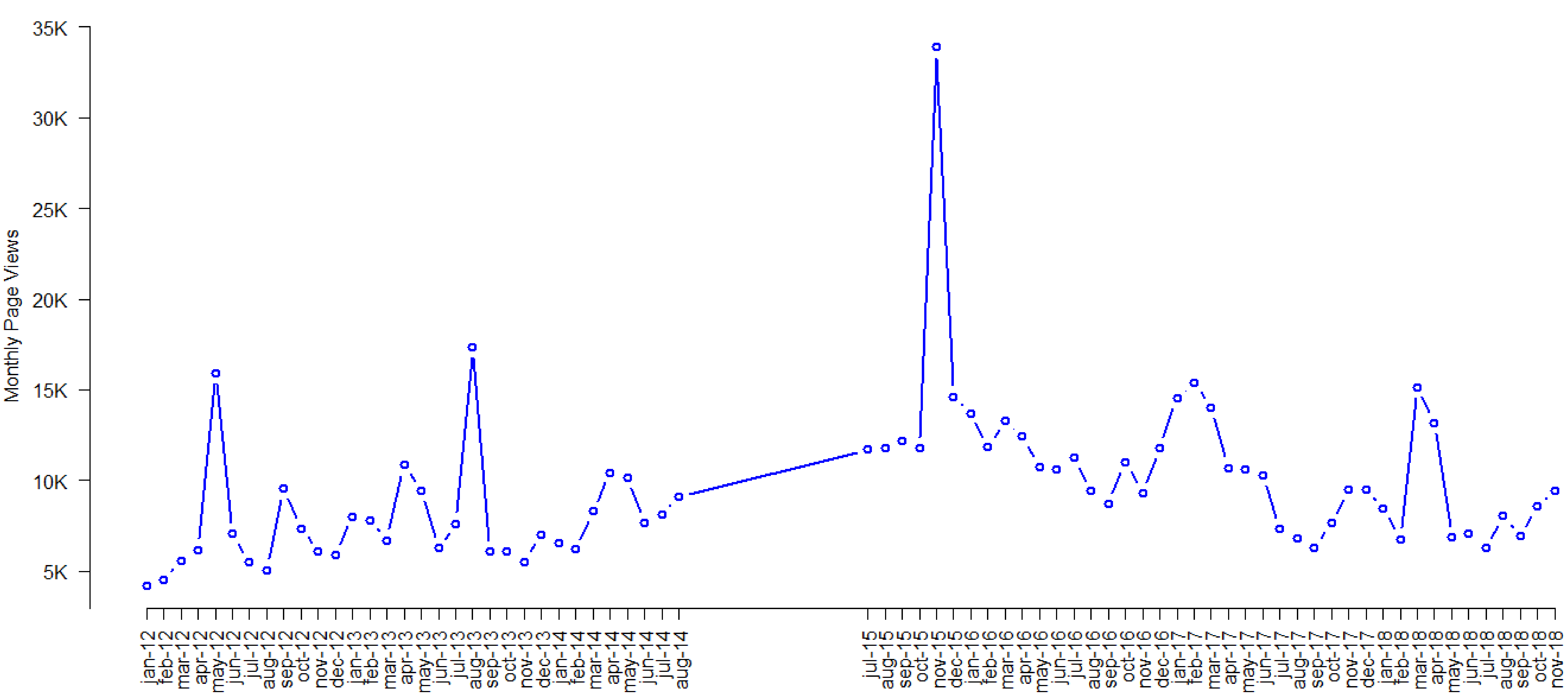


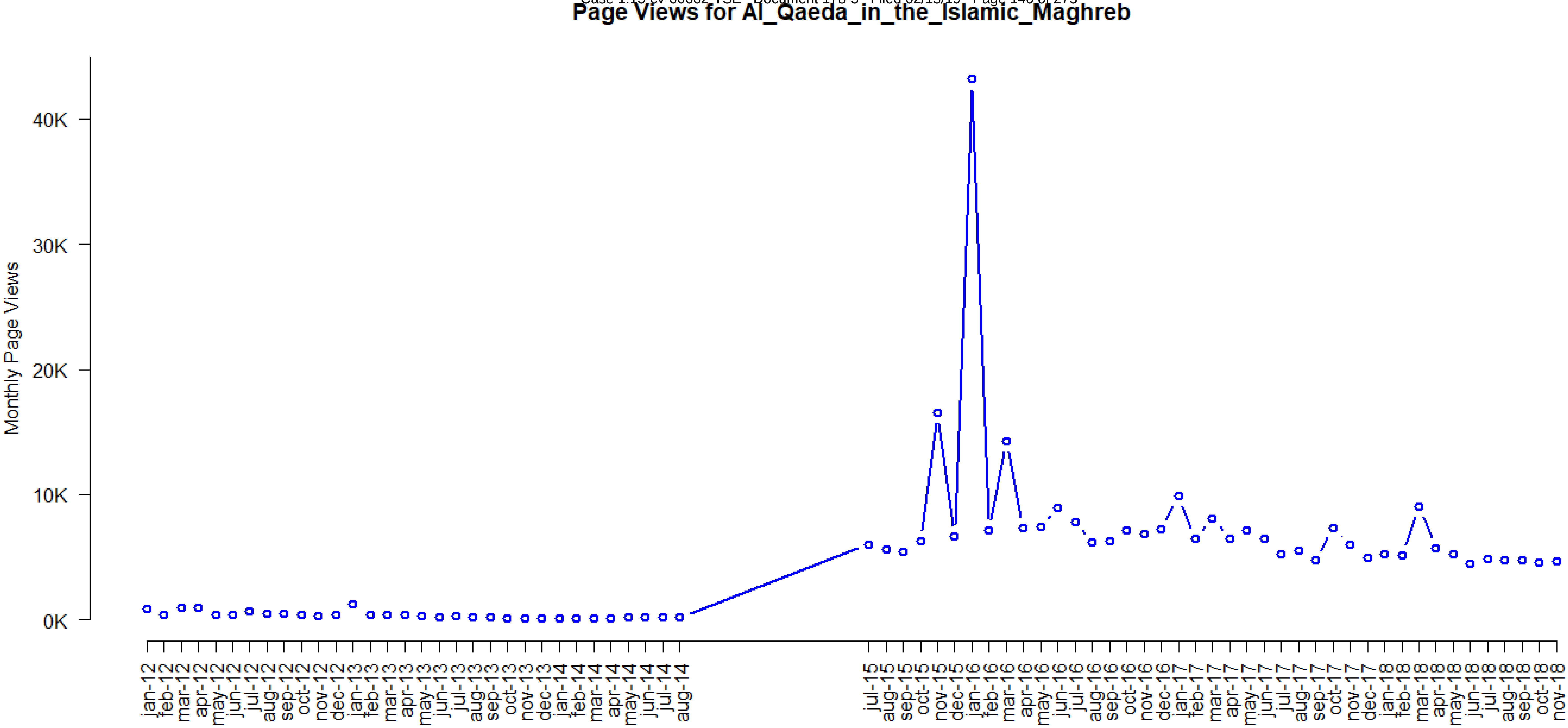
## Page Views for agro




Page Views for Al_Qaeda
Monthly Page Views
400K
300K
200K
100K
0K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14
jul-15
aug-15
sep-15
oct-15
nov-15
dec-15
jan-16
feb-16
mar-16
apr-16
may-16
jun-16
jul-16
aug-16
sep-16
oct-16
nov-16
dec-16
jan-17
feb-17
mar-17
apr-17
may-17
jun-17
jul-17
aug-17
sep-17
oct-17
nov-17
dec-17
jan-18
feb-18
mar-18
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18

Page Views for AL_Qaeda_in_the_Arabian_Peninsula




Page Views for Al_Qaeda_in_the_Islamic_Maghreb
Monthly Page Views
40K
30K
20K
10K
0K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14
jul-15
aug-15
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nov-15
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feb-16
mar-16
apr-16
may-16
jun-16
jul-16
aug-16
sep-16
oct-16
nov-16
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mar-17
apr-17
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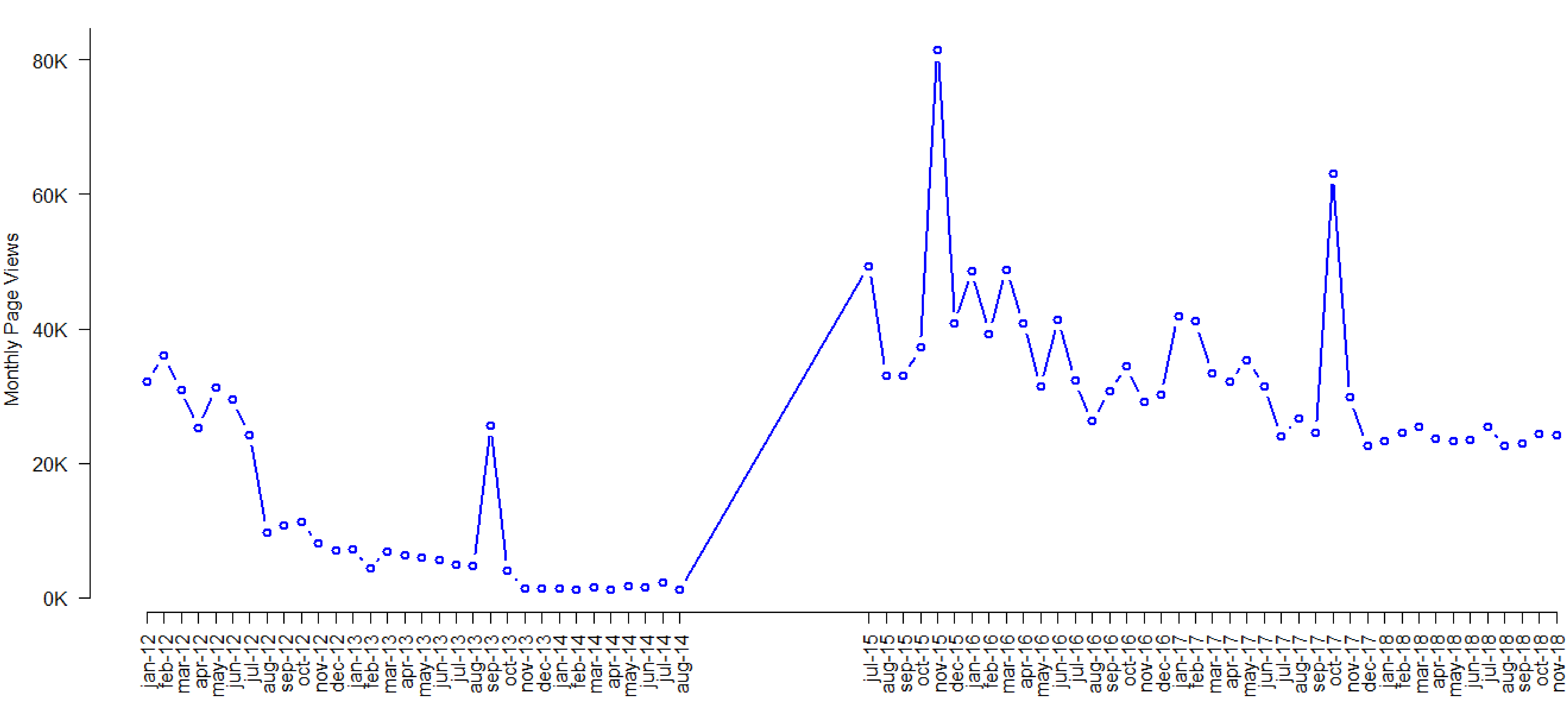
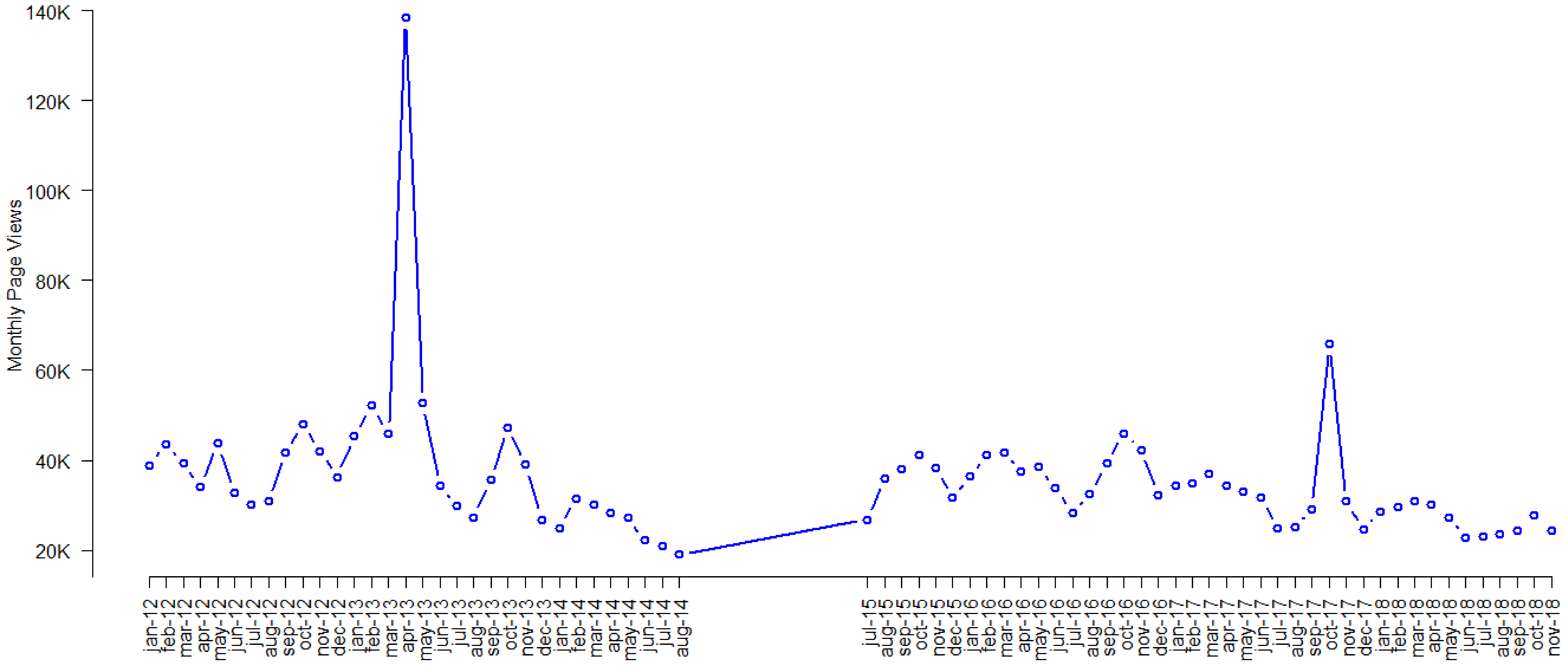
nov-17
dec-17
jan-18
feb-18
mar-18
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18

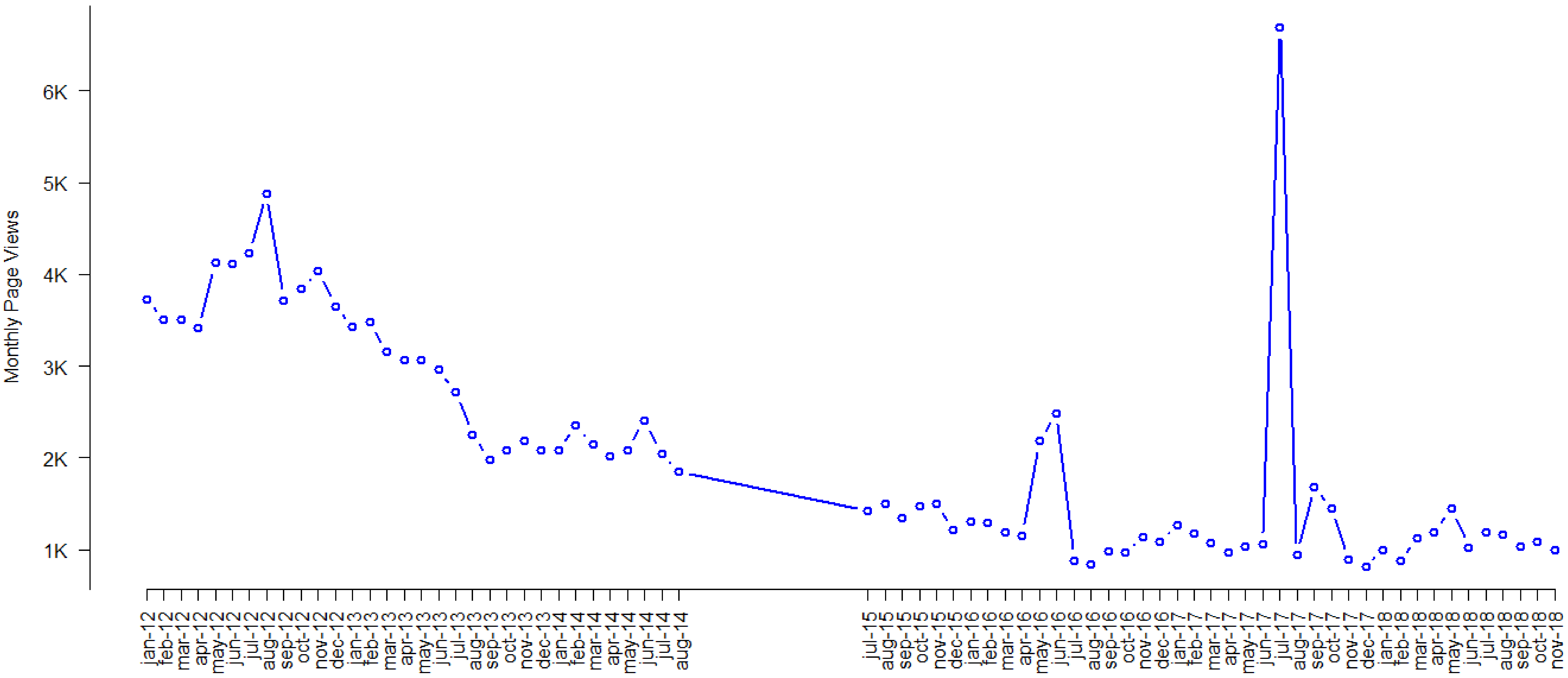
Page Views for Al_Shabaab

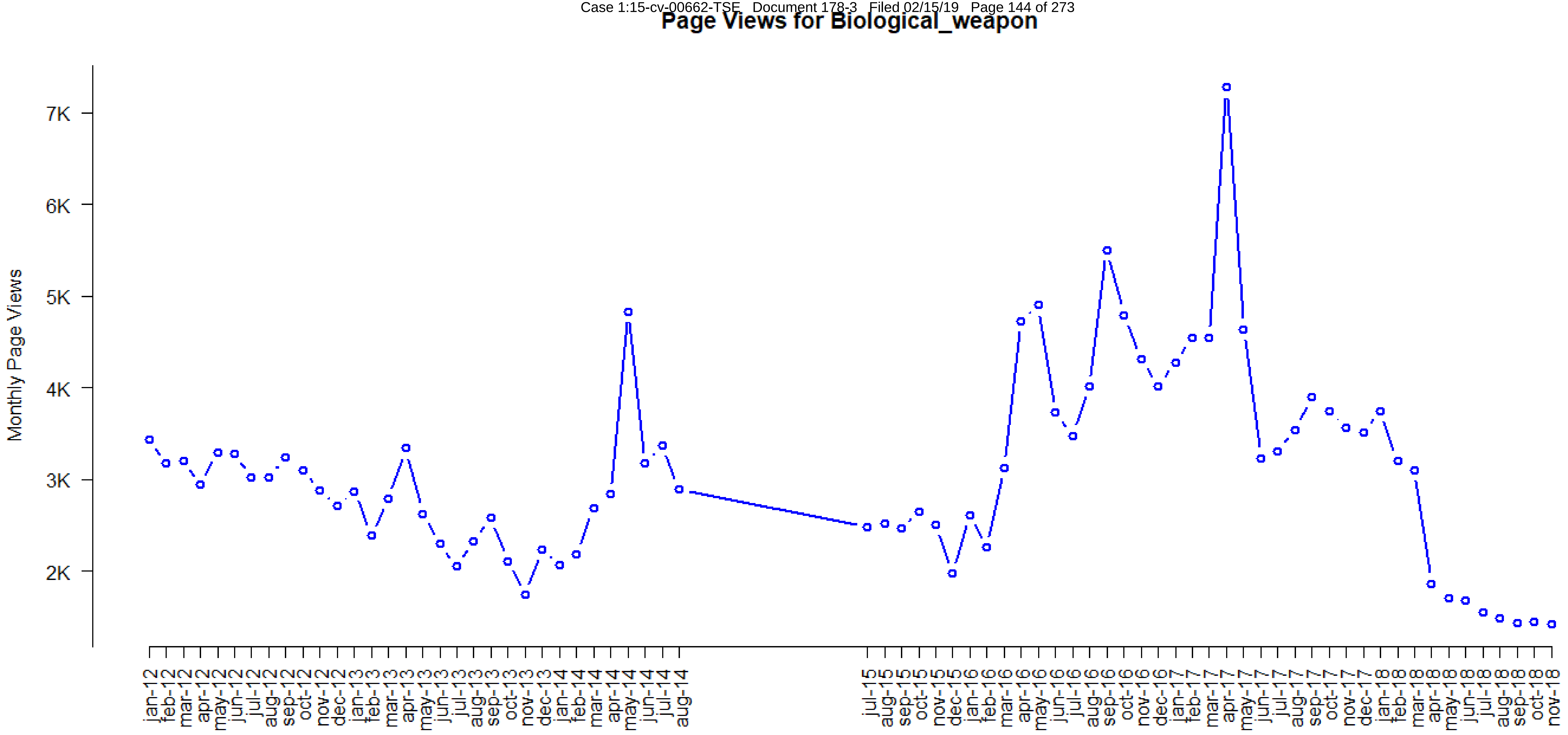


# Page Views for Ammonium_nitrate



# Page Views for attack




Page Views for Biological_weapon
Monthly Page Views
7K
6K
5K
4K
3K
2K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
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jan-18
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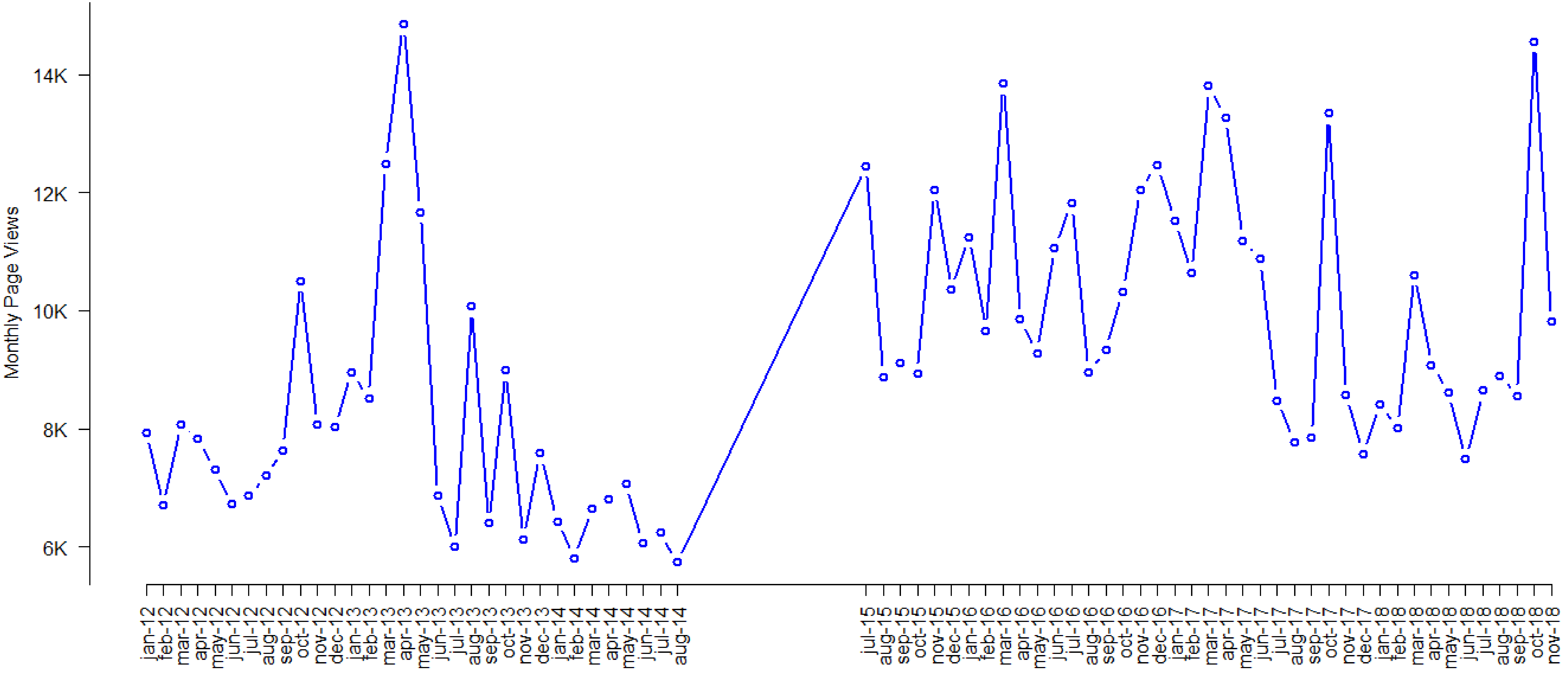
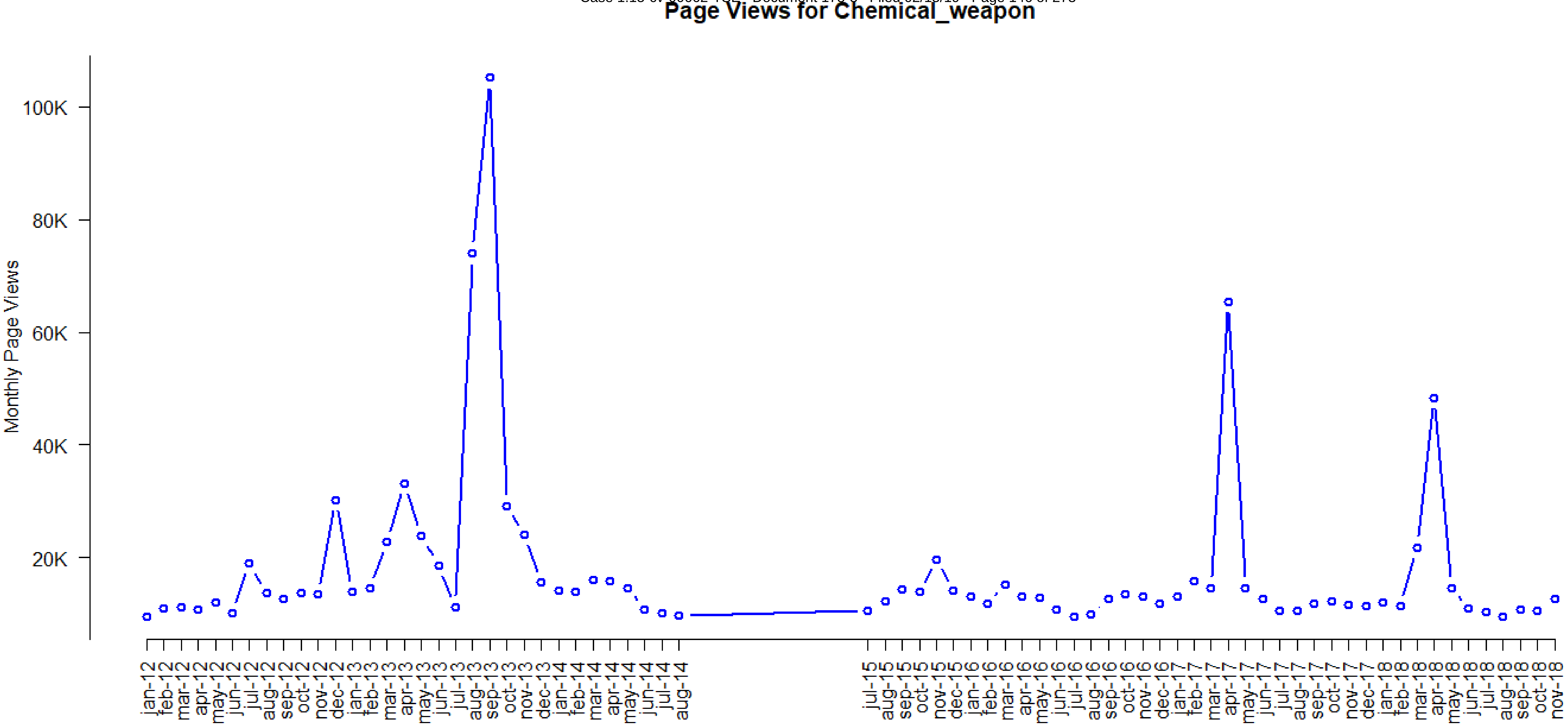
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18

# Page Views for Car_bomb




Page Views for Chemical_weapon
Monthly Page Views
100K
80K
60K
40K
20K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
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mar-13
apr-13
may-13
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aug-13
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mar-14
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jun-16
jul-16
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nov-16
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jan-17
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mar-17
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jun-17
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oct-17
nov-17
dec-17
jan-18
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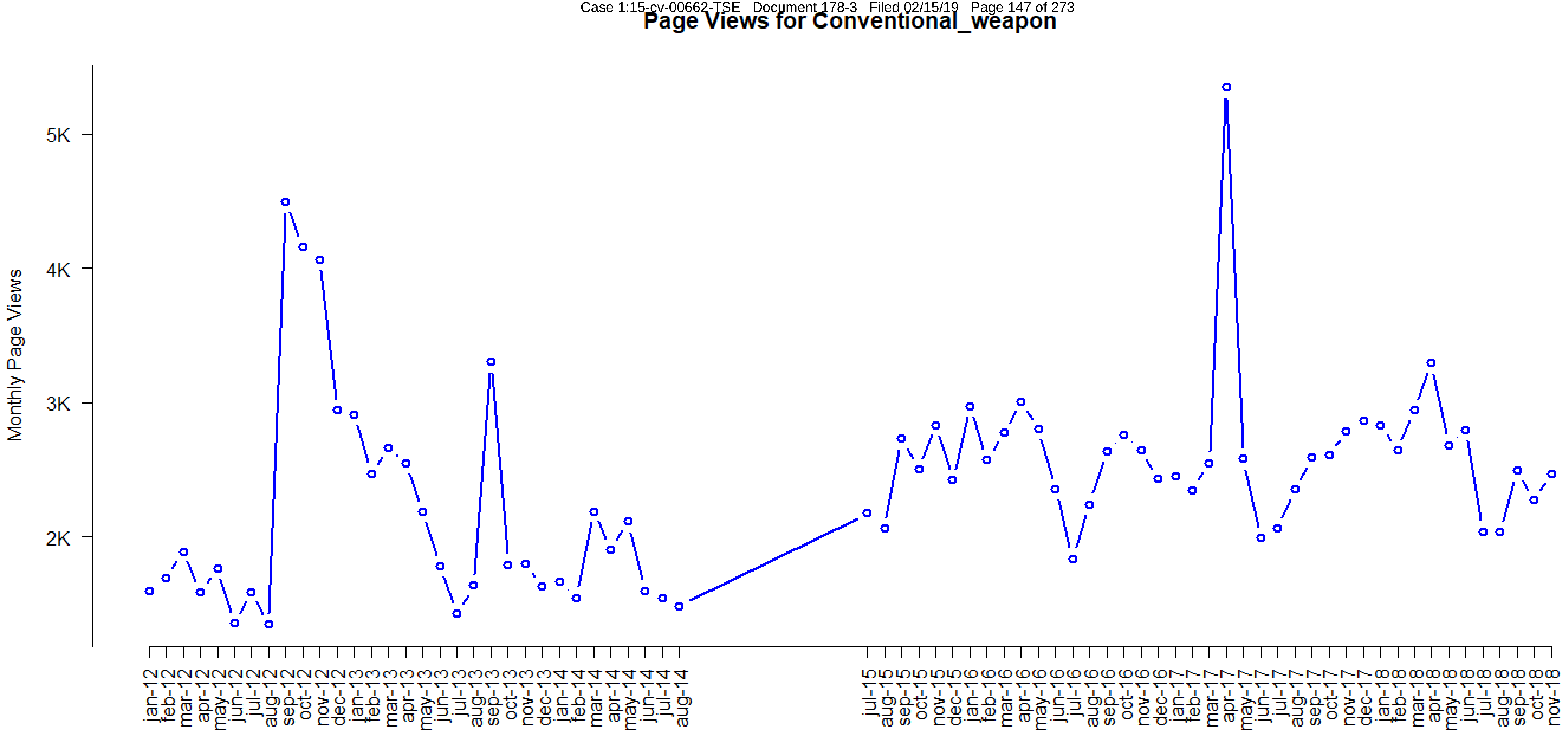
mar-18
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18


Page Views for Conventional_weapon
Monthly Page Views
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3K
2K
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feb-12
mar-12
apr-12
may-12
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feb-13
mar-13
apr-13
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jul-13
aug-13
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oct-17
nov-17
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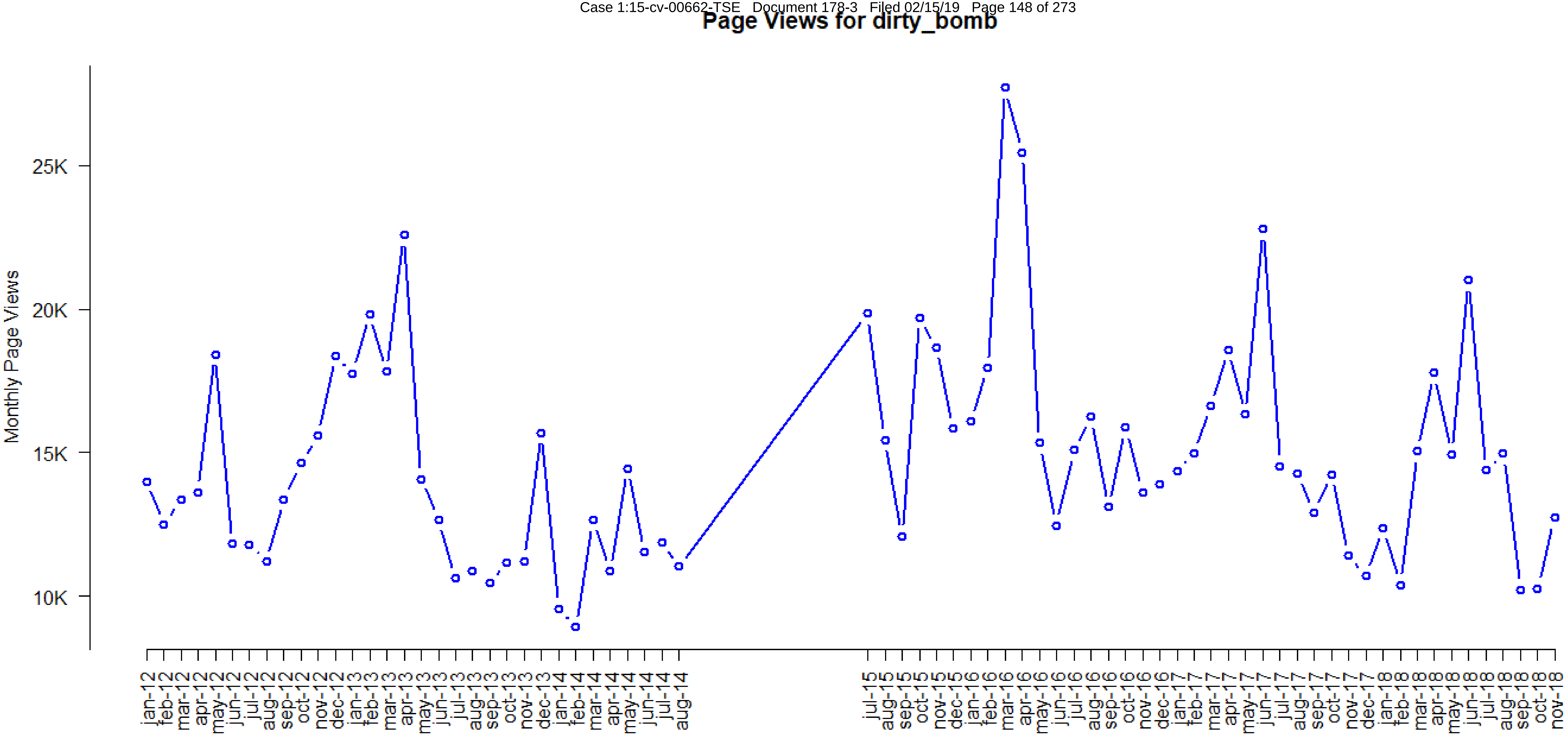
jan-18
feb-18
mar-18
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18


Page Views for dirty_bomb
Monthly Page Views
25K
20K
15K
10K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
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apr-13
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aug-14
jul-15
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jul-17
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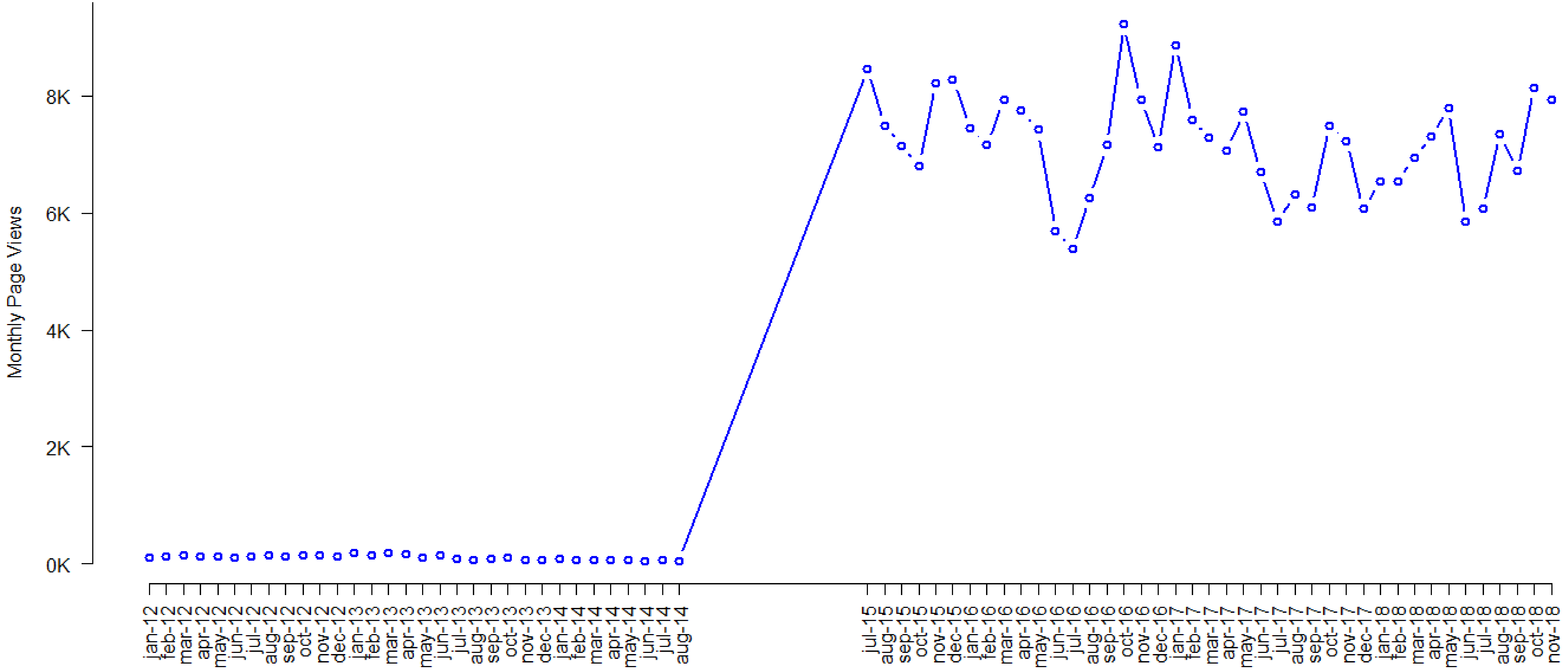
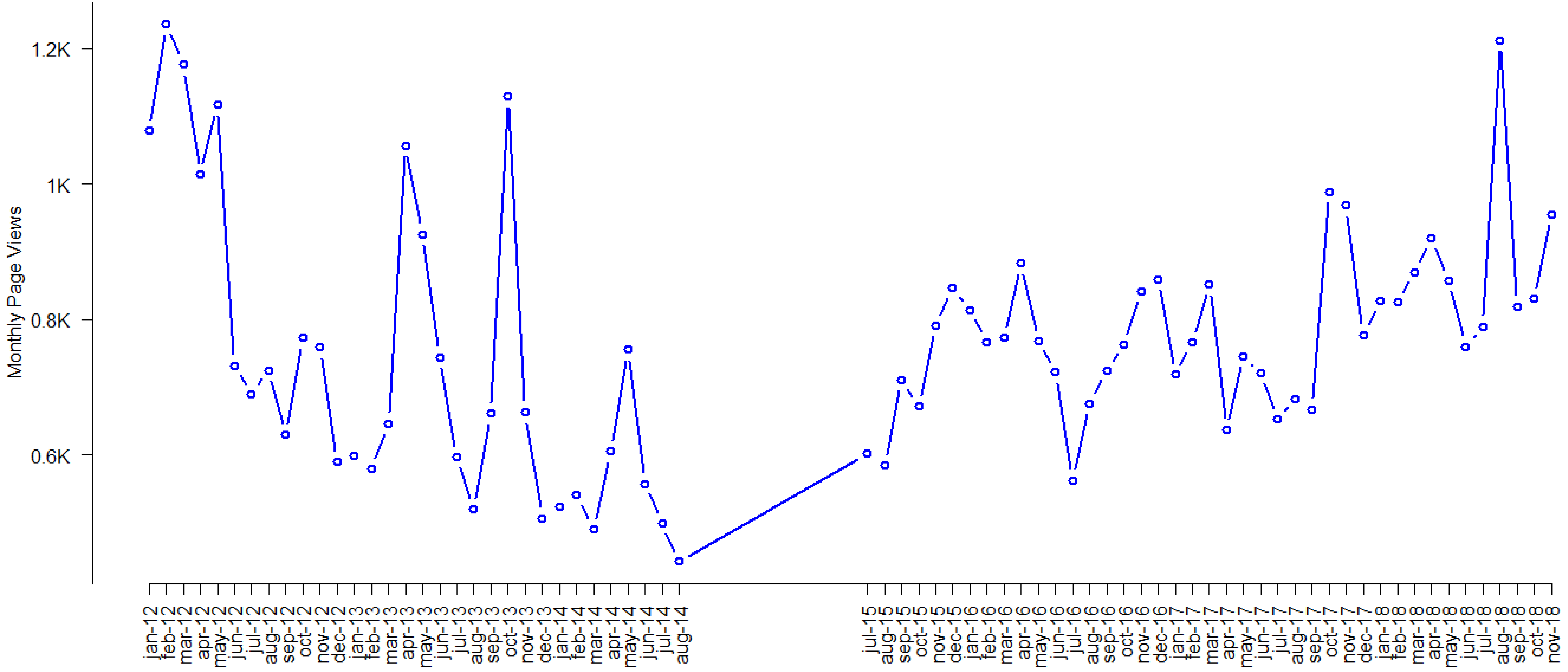
oct-17
nov-17
dec-17
jan-18
feb-18
mar-18
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18

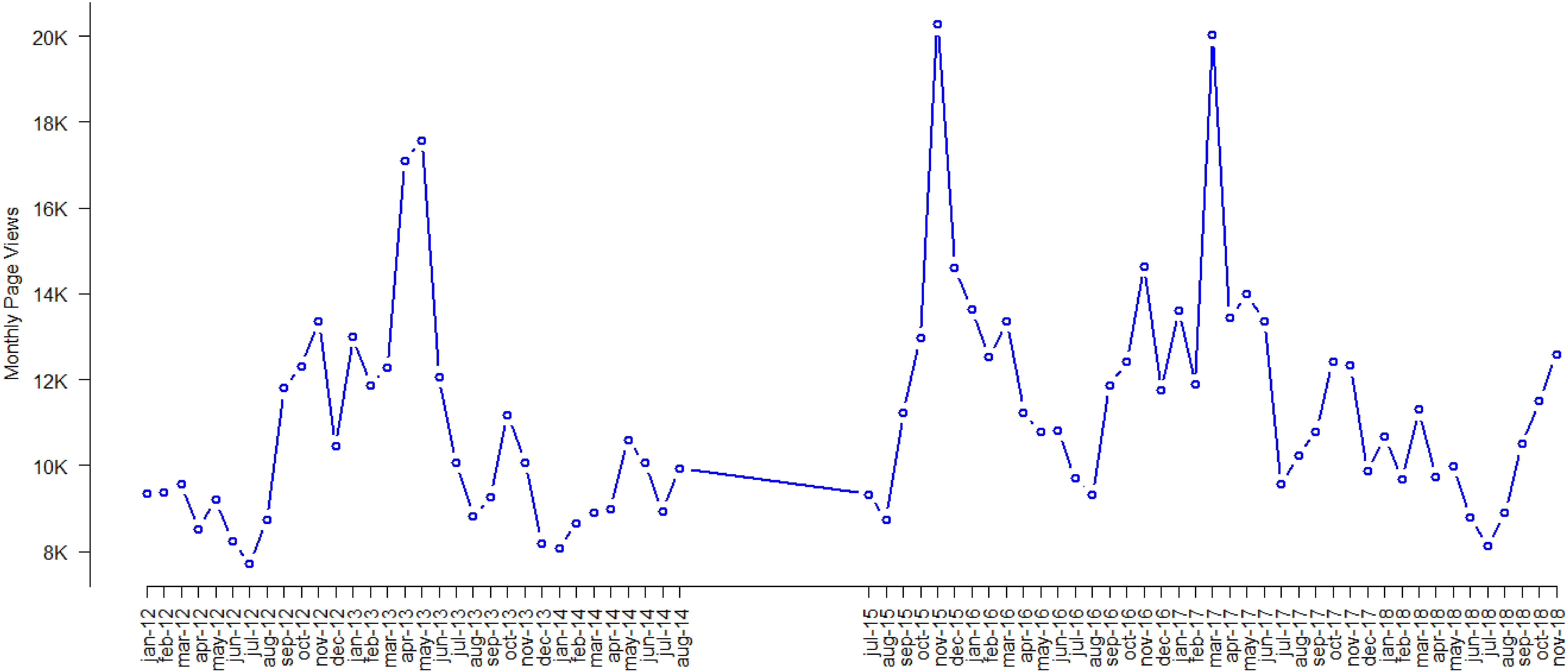
# Page Views for Eco_terrorism



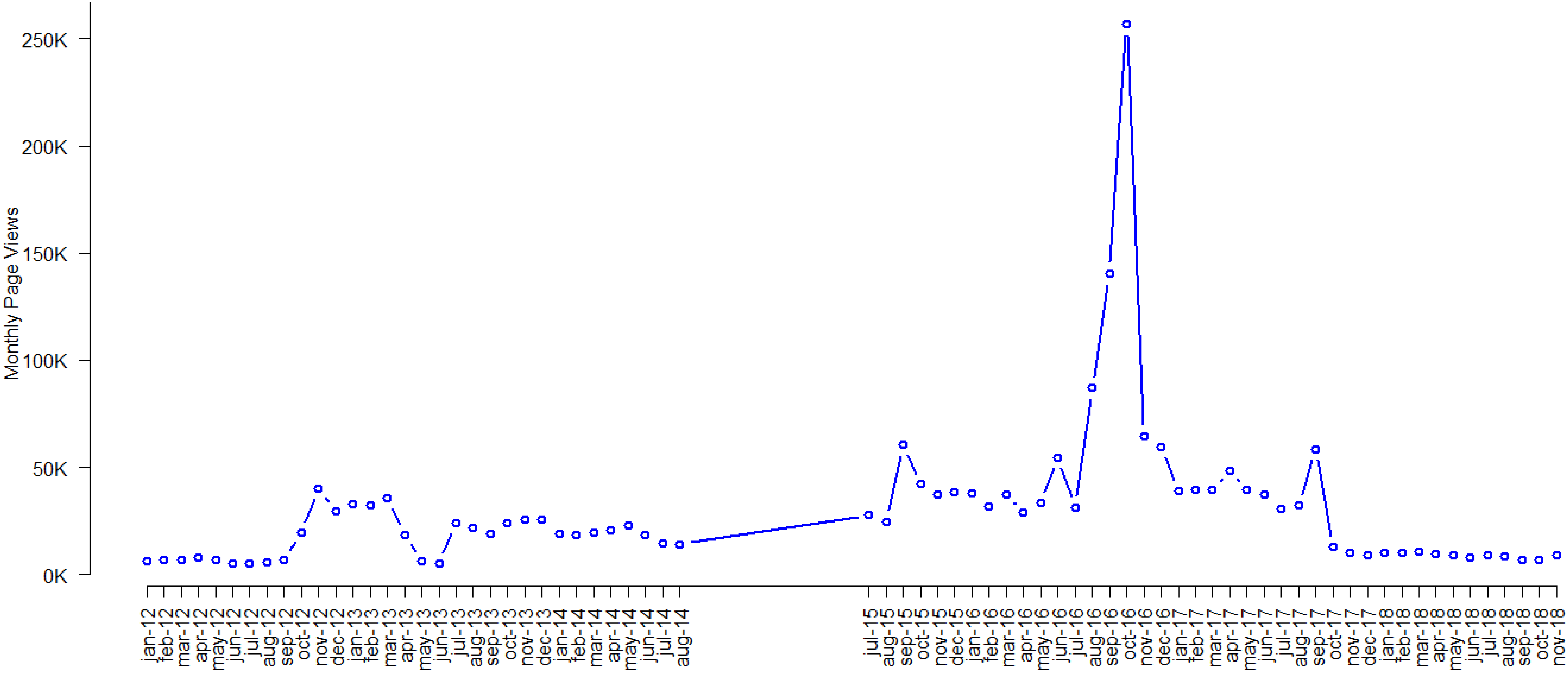
## Page Views for Environmental_terrorist_NA_ism



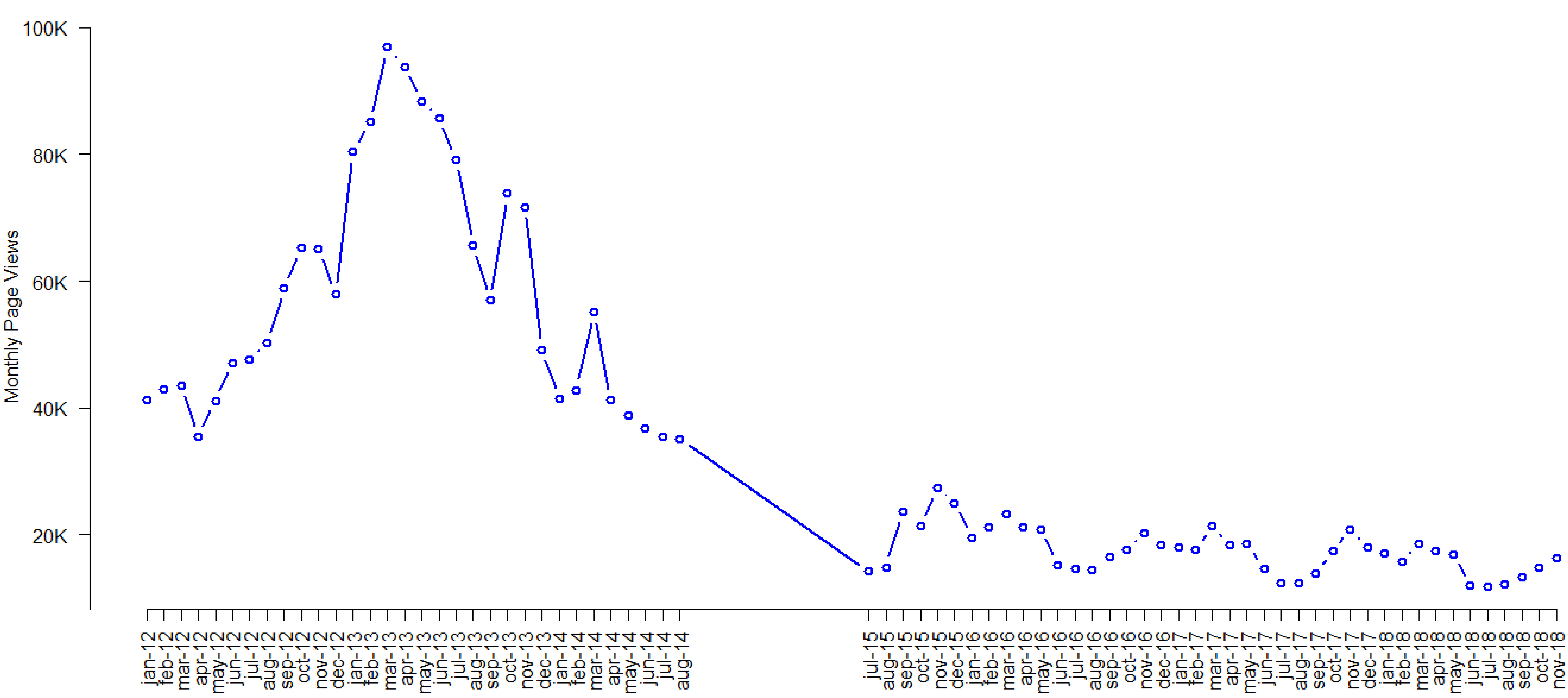
## Page Views for Extremism



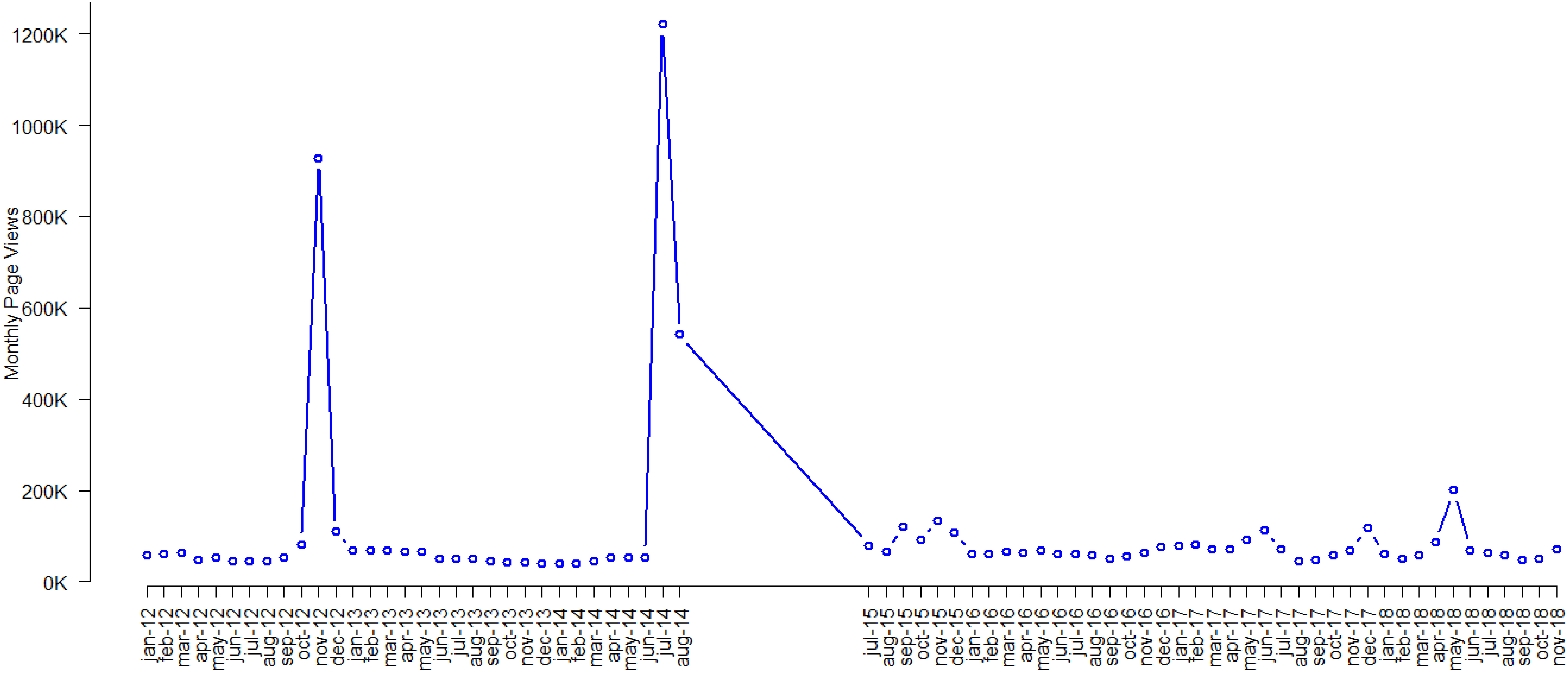
Page Views for FARC



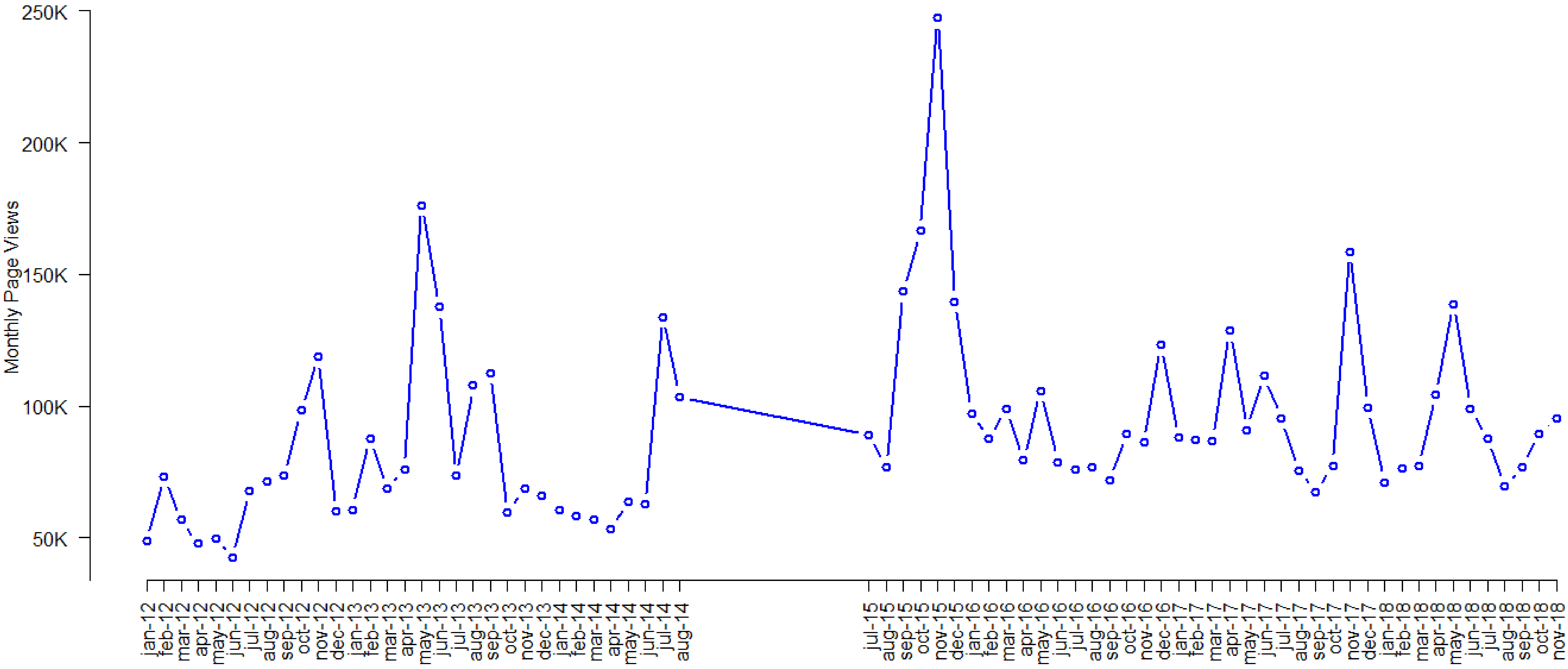
Page Views for Fundamentalism



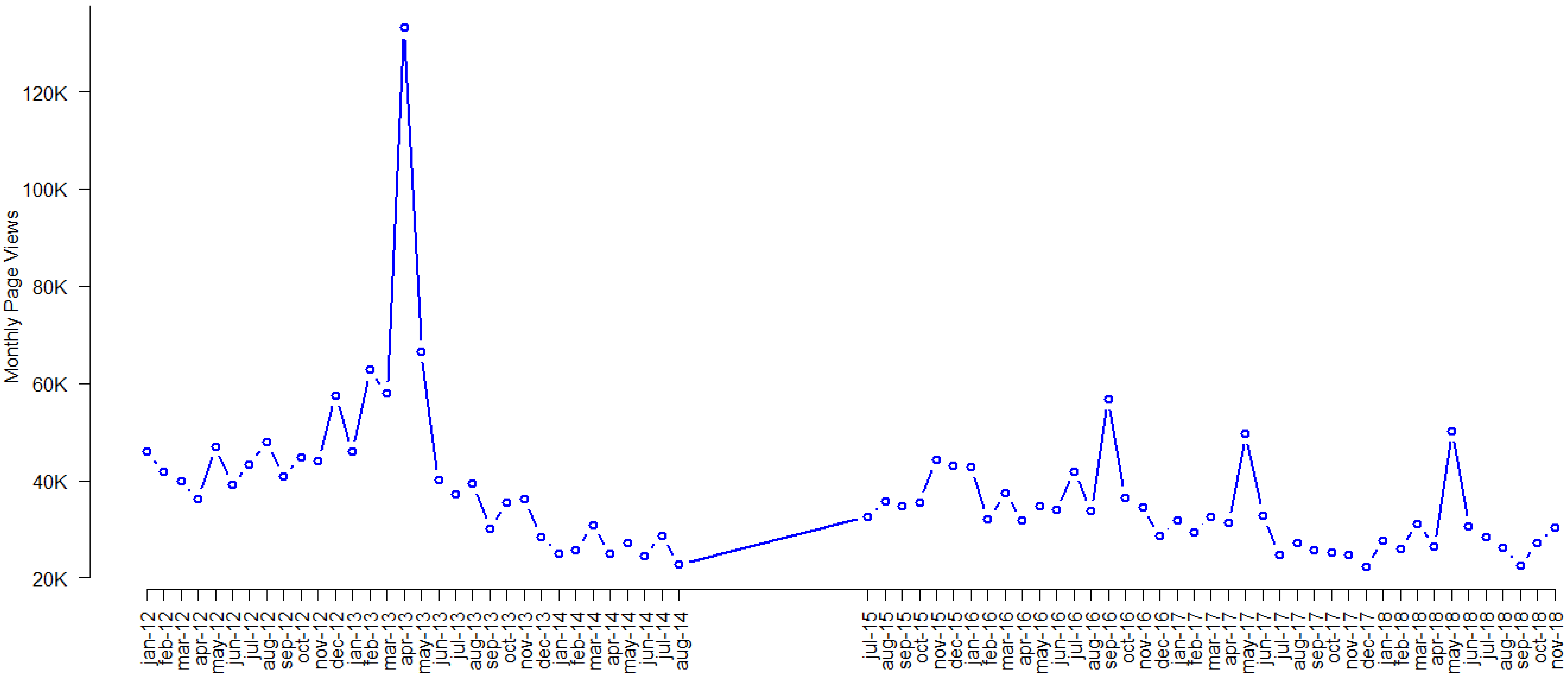
## Page Views for Hamas



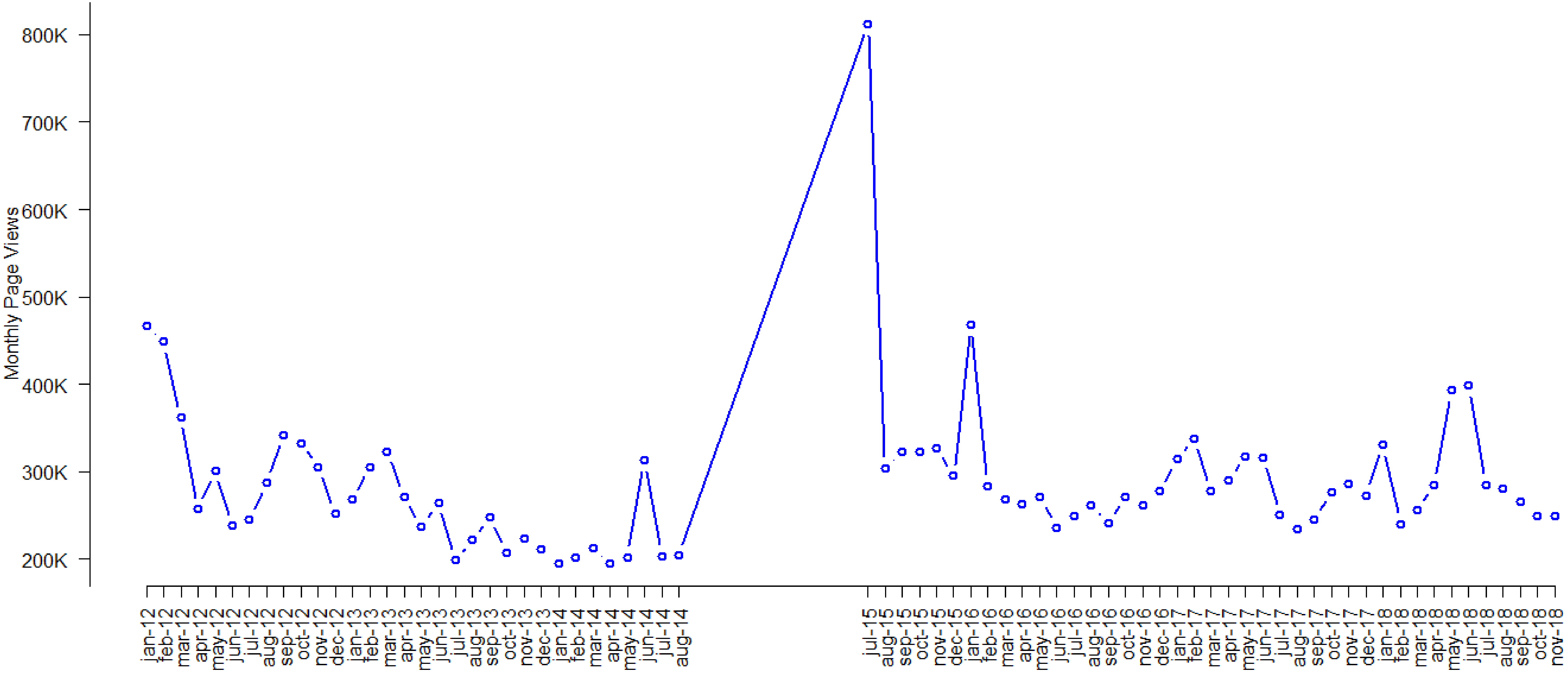
## Page Views for Hezbollah



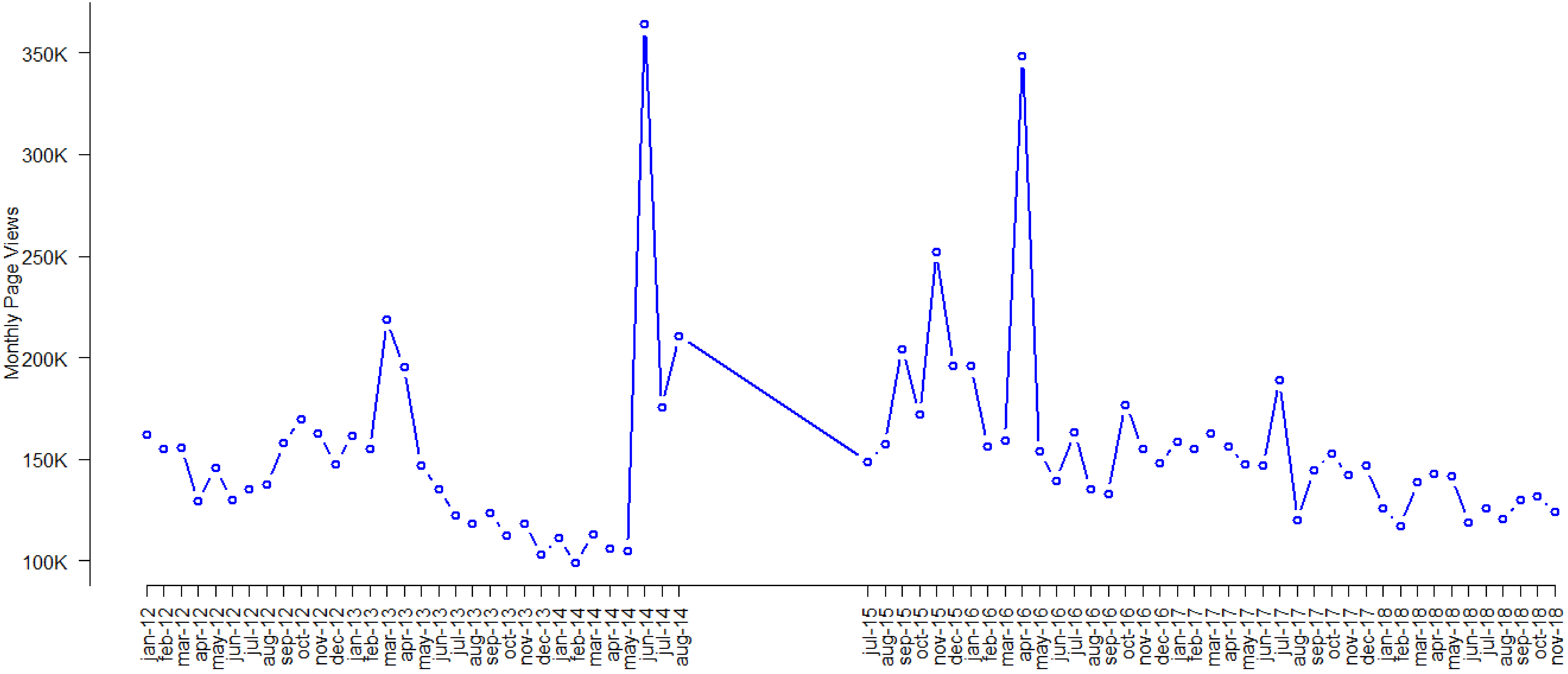
Page Views for Improvised_explosive_device



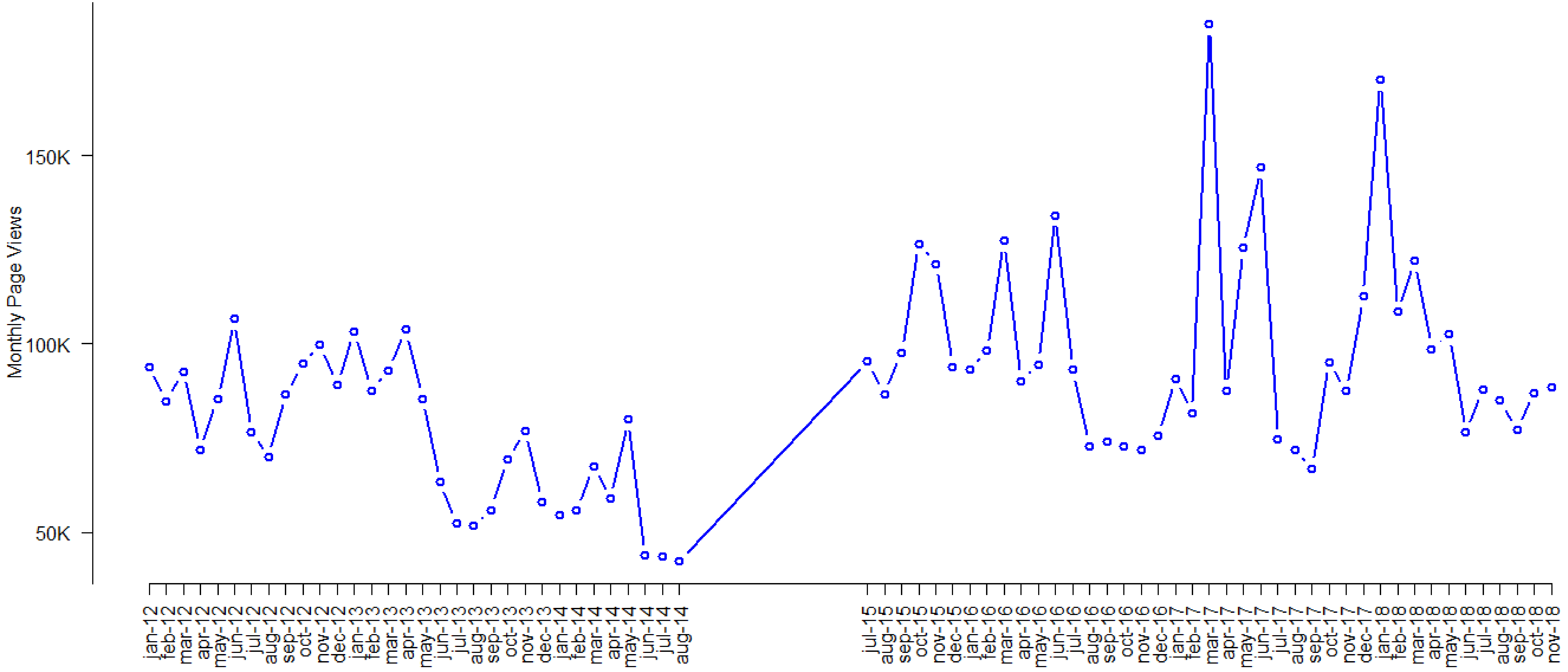
# Page Views for Iran



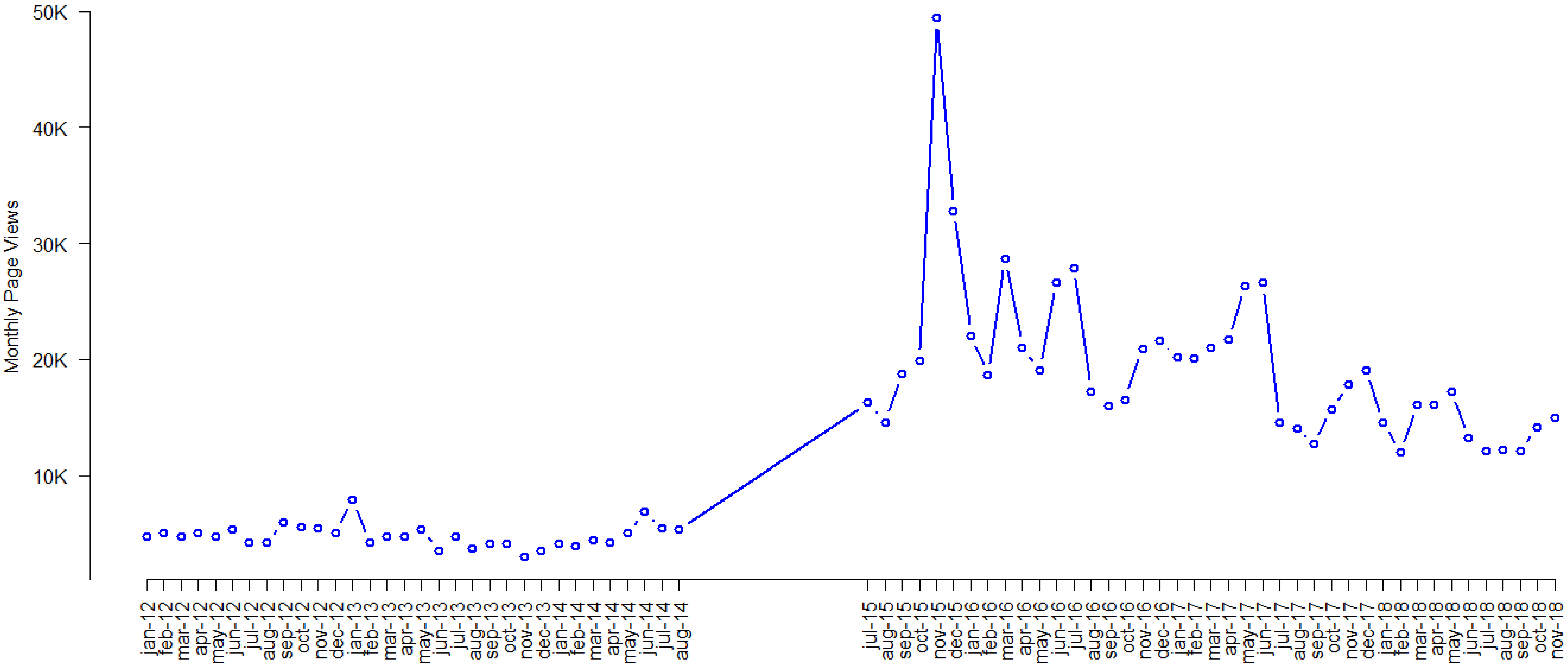
## Page Views for Iraq



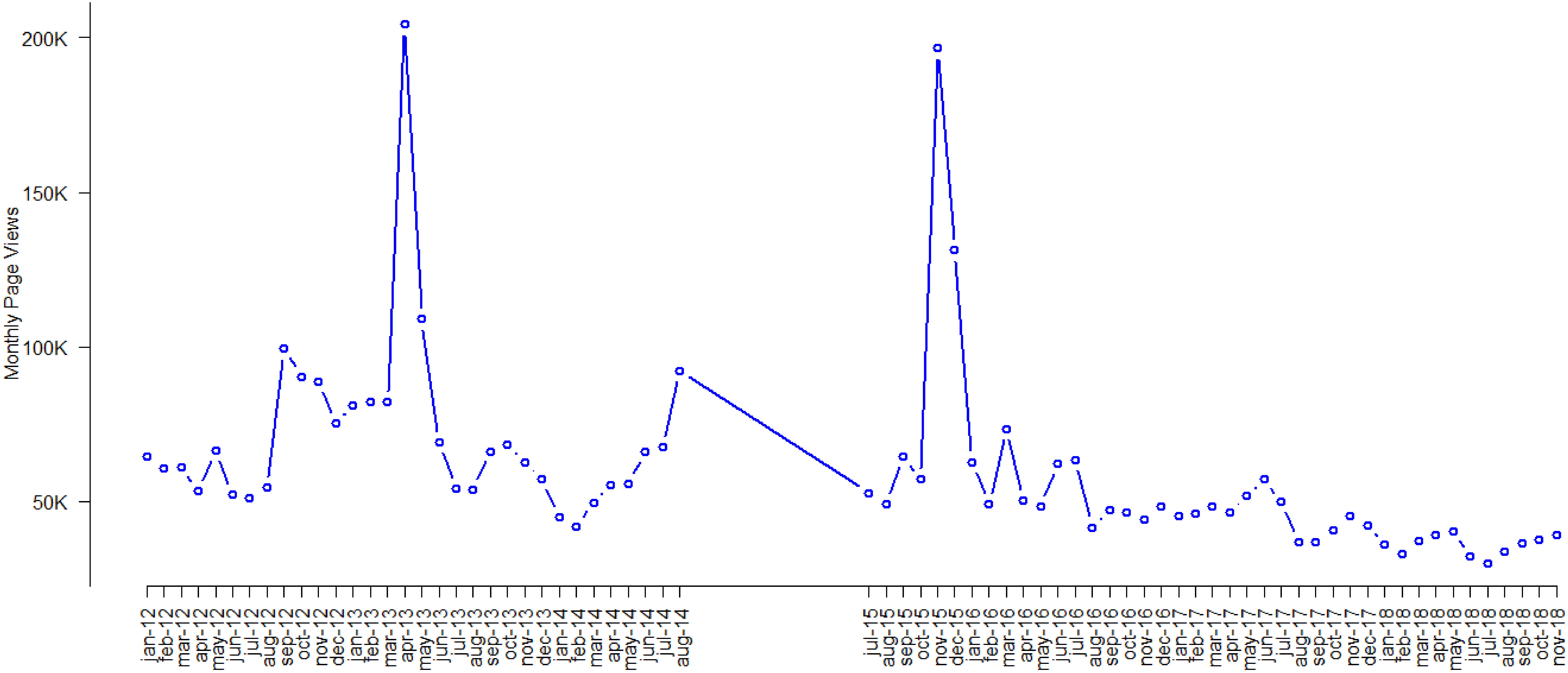
## Page Views for Irish_Republican_Army



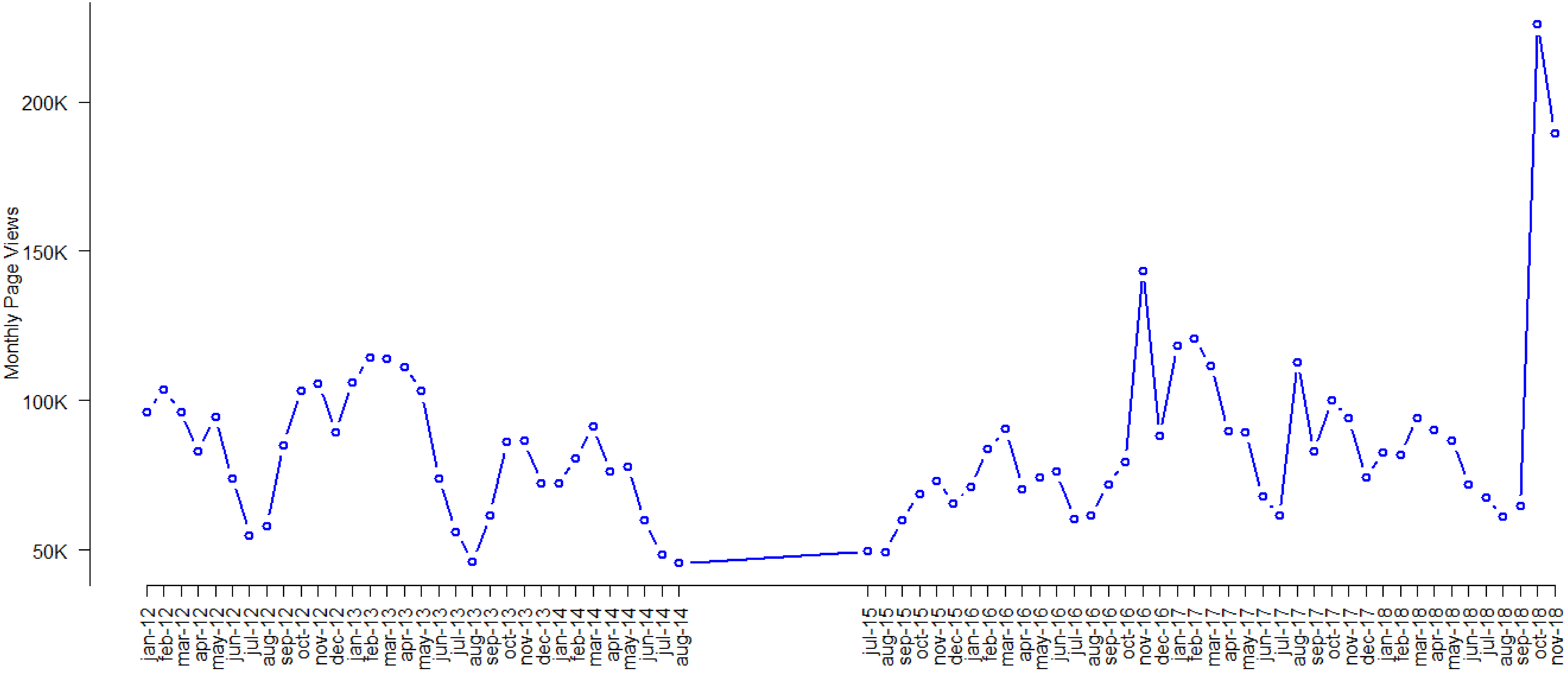
# Page Views for Islamist



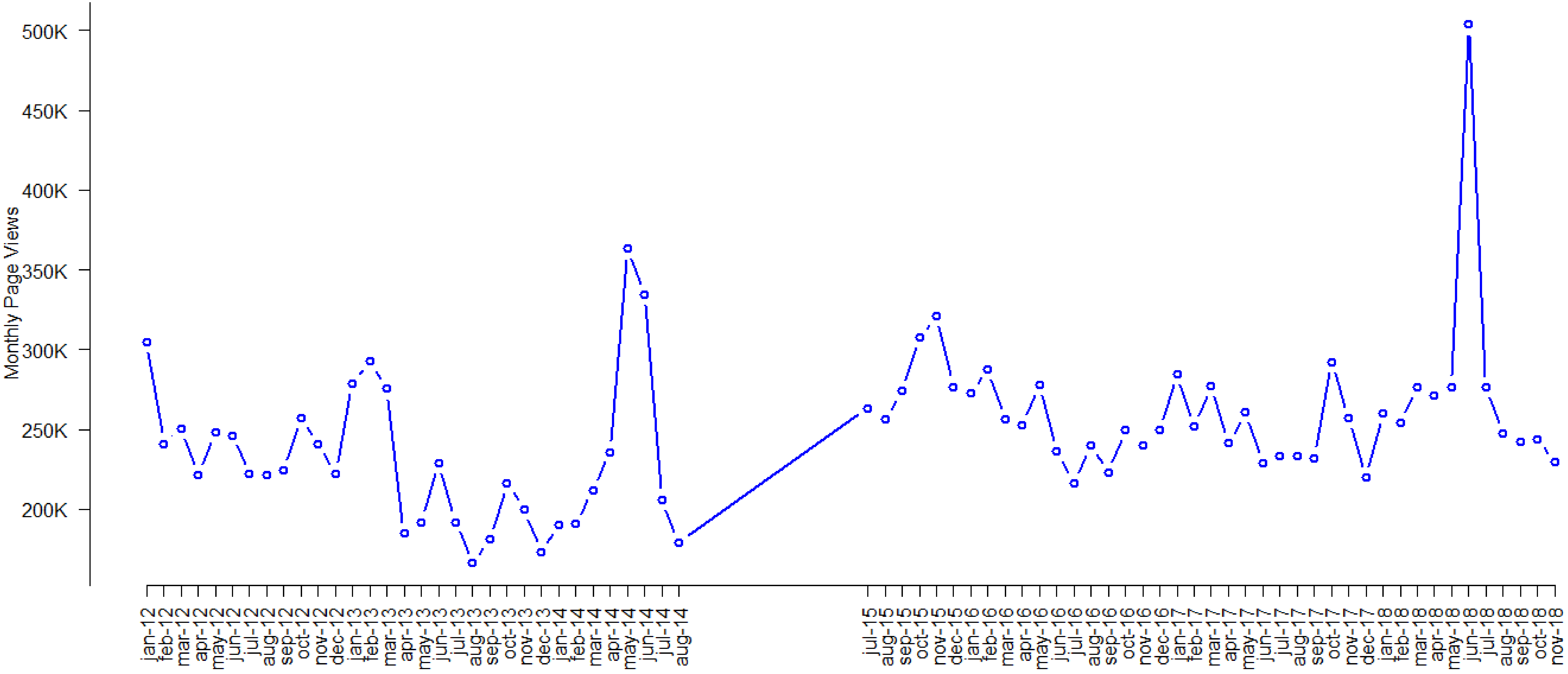
## Page Views for Jihad



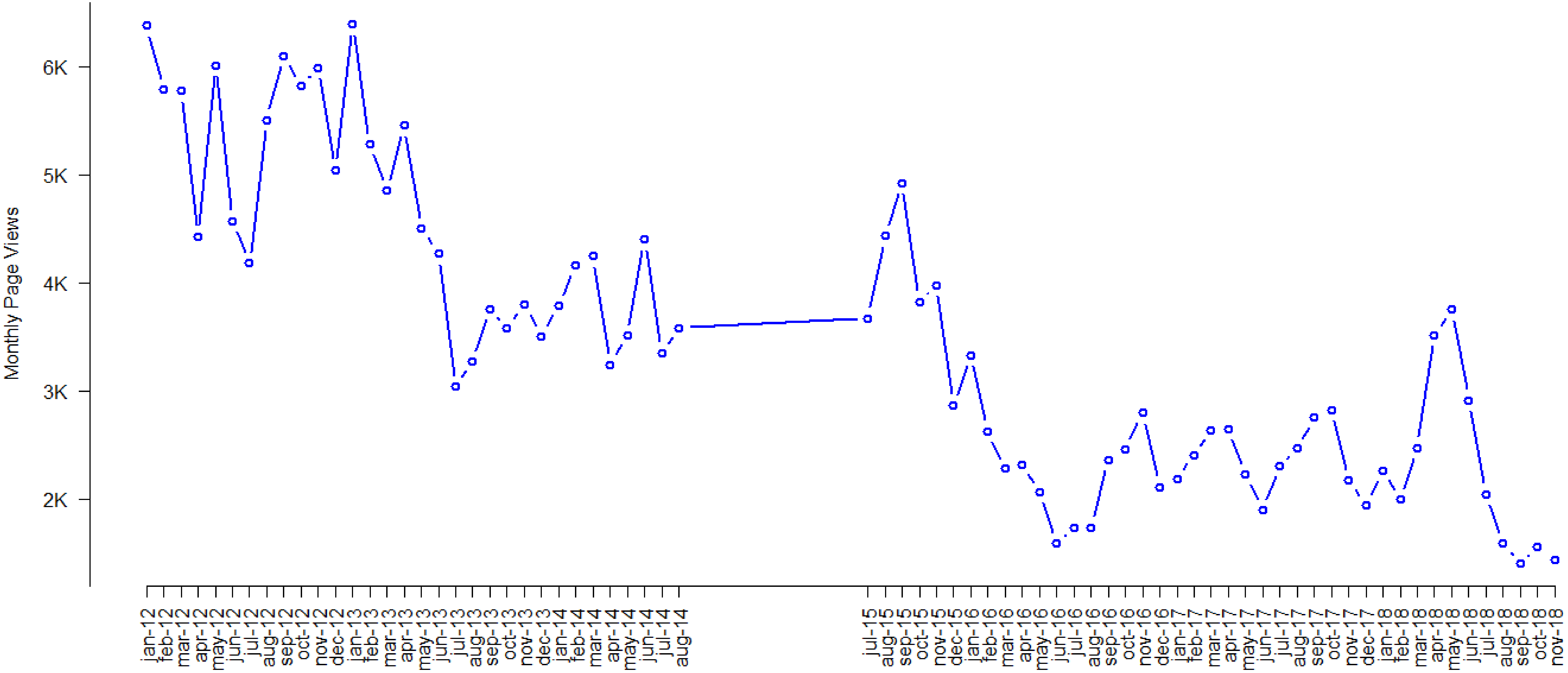
# Page Views for nationalism



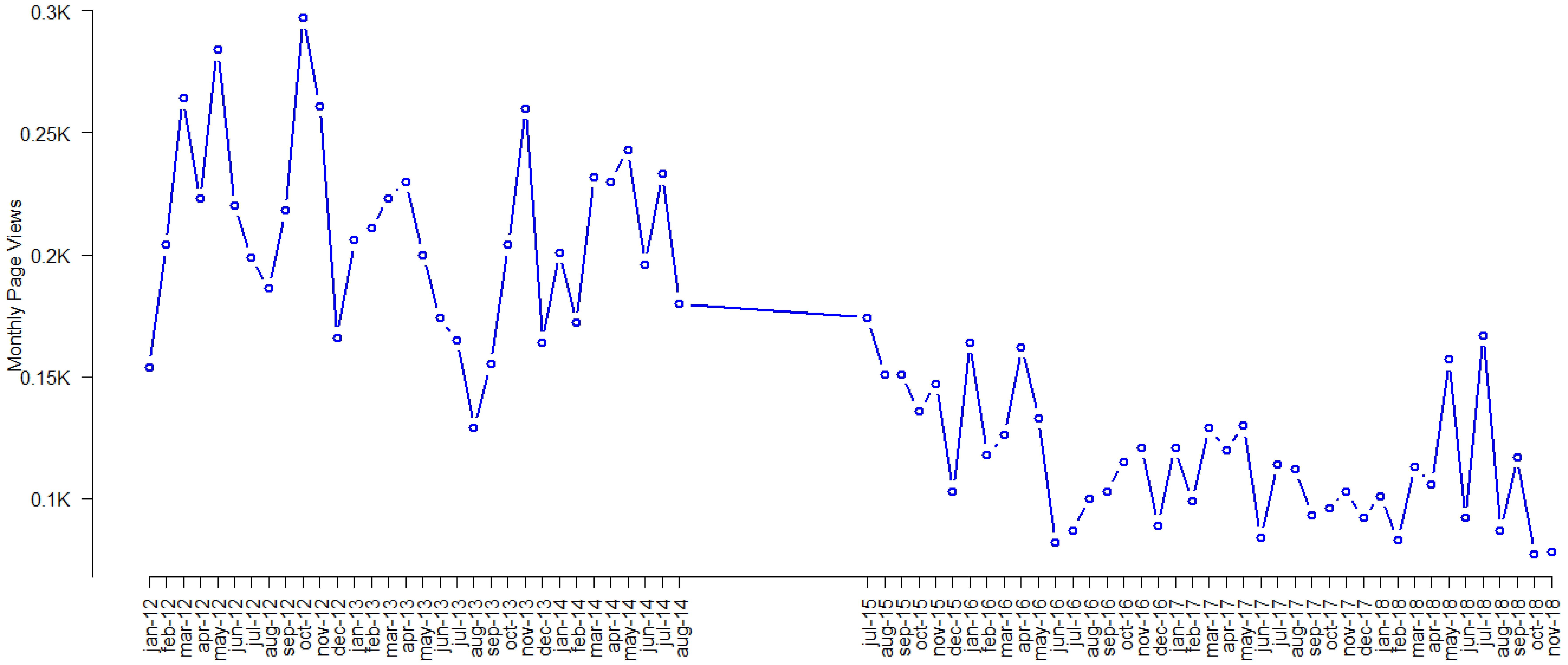
# Page Views for Nigeria



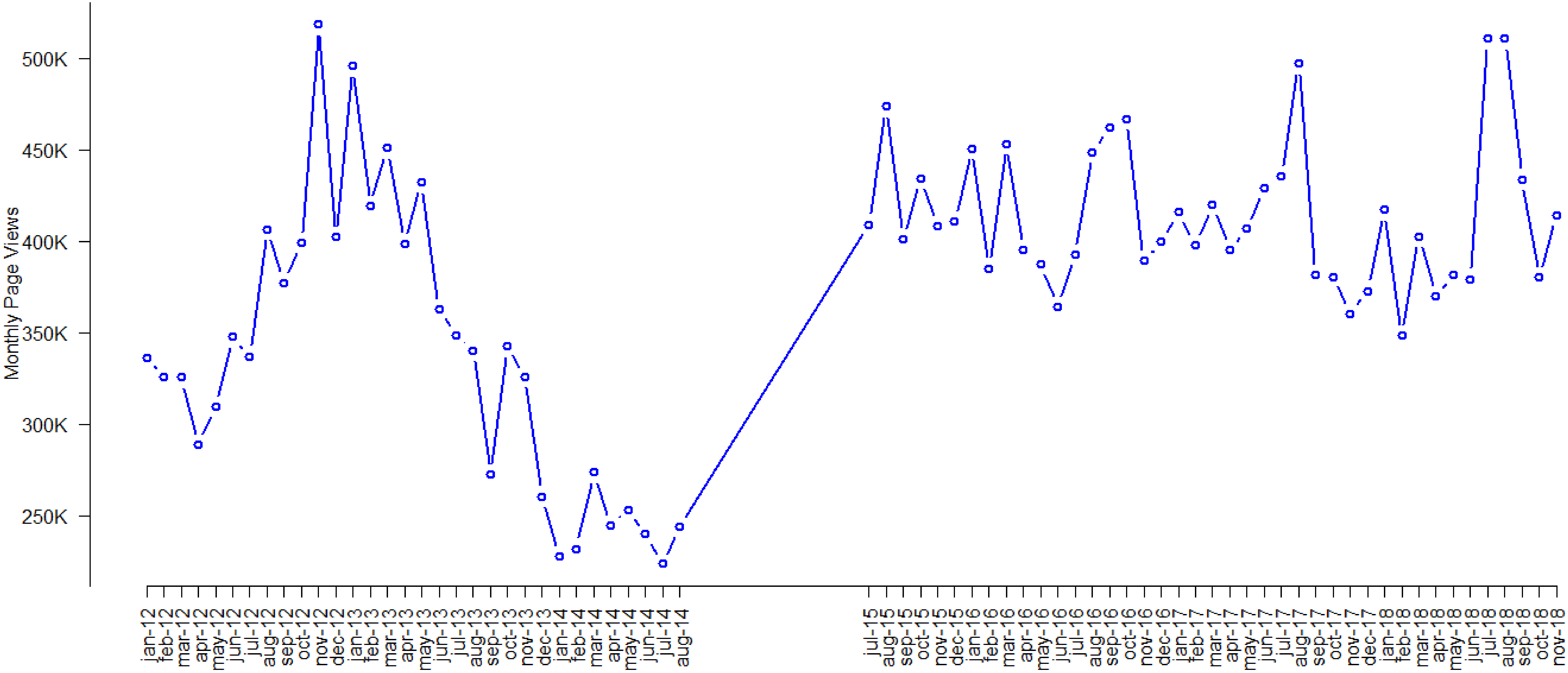
# Page Views for Nuclear



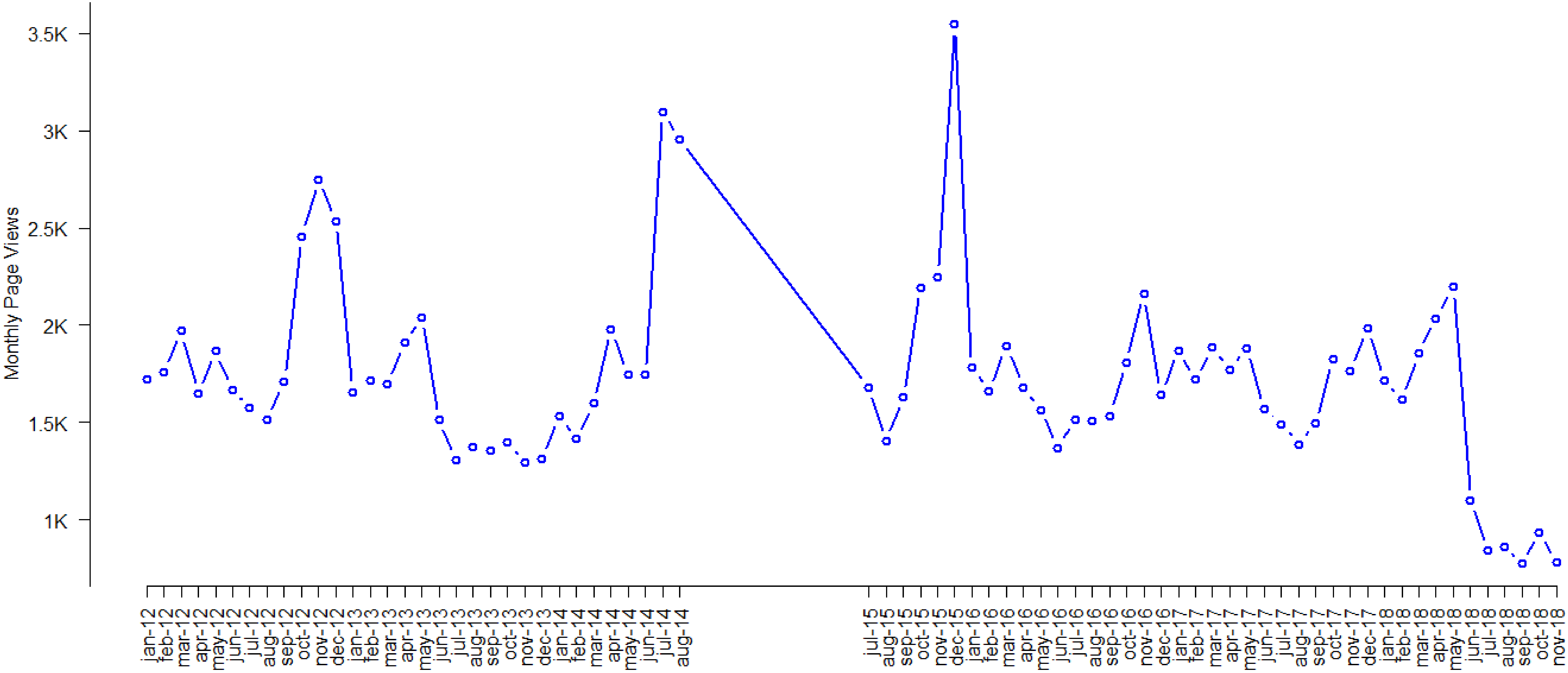
## Page Views for Nuclear_Enrichment



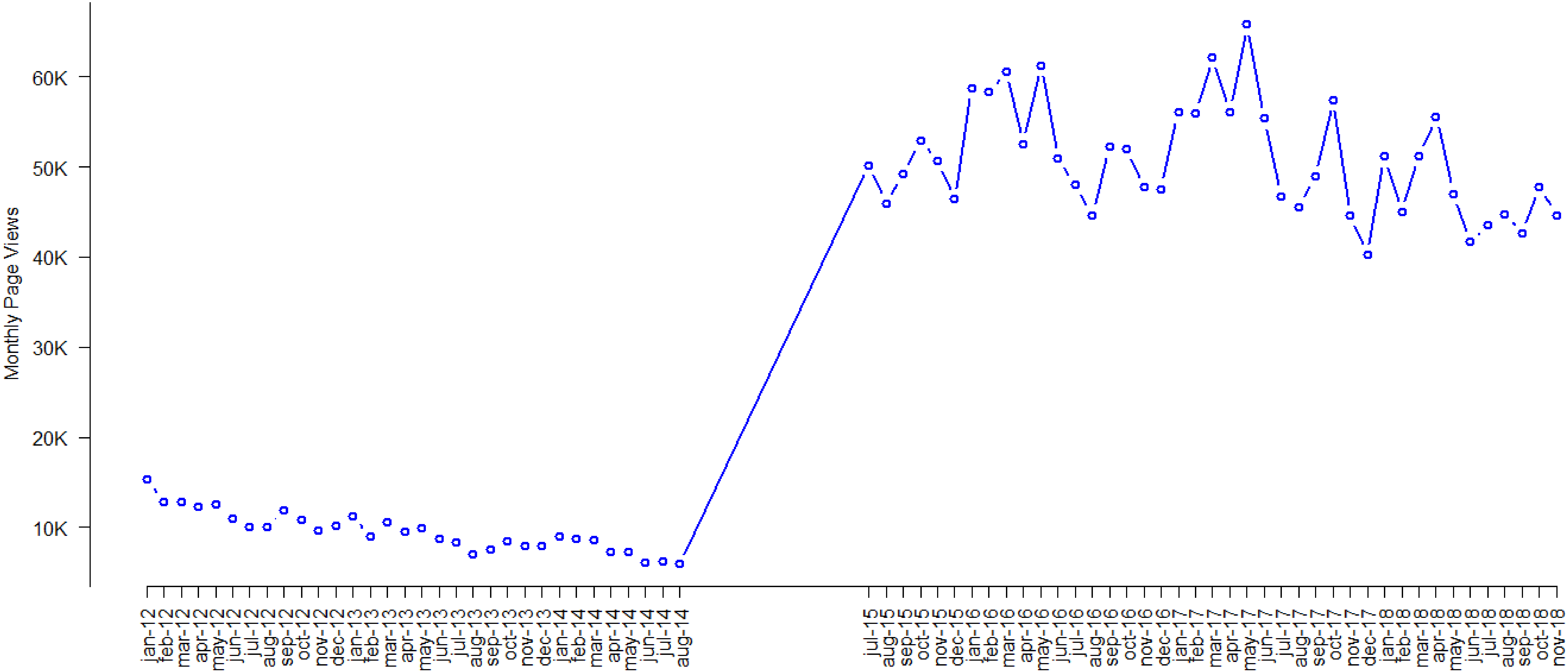
# Page Views for Pakistan



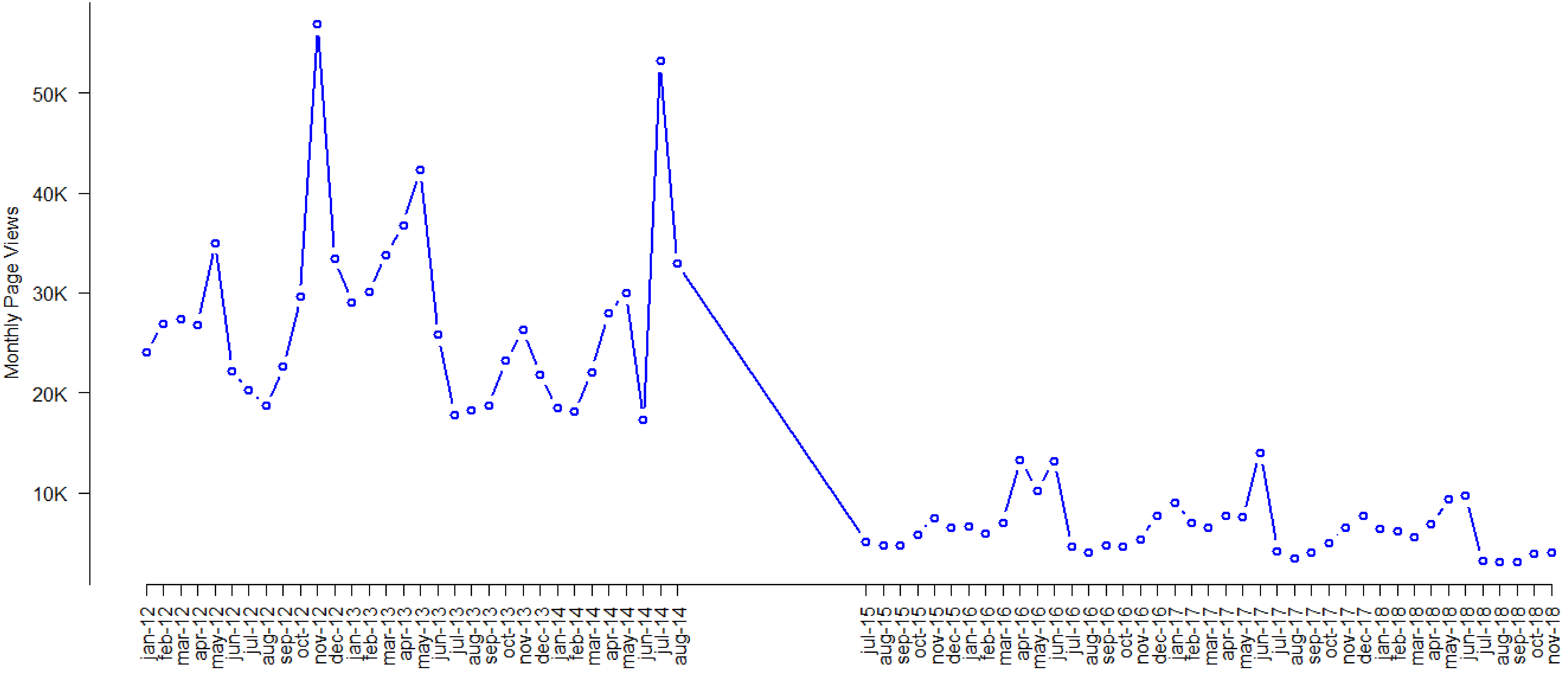
Page Views for Palestine_Liberation_Fron

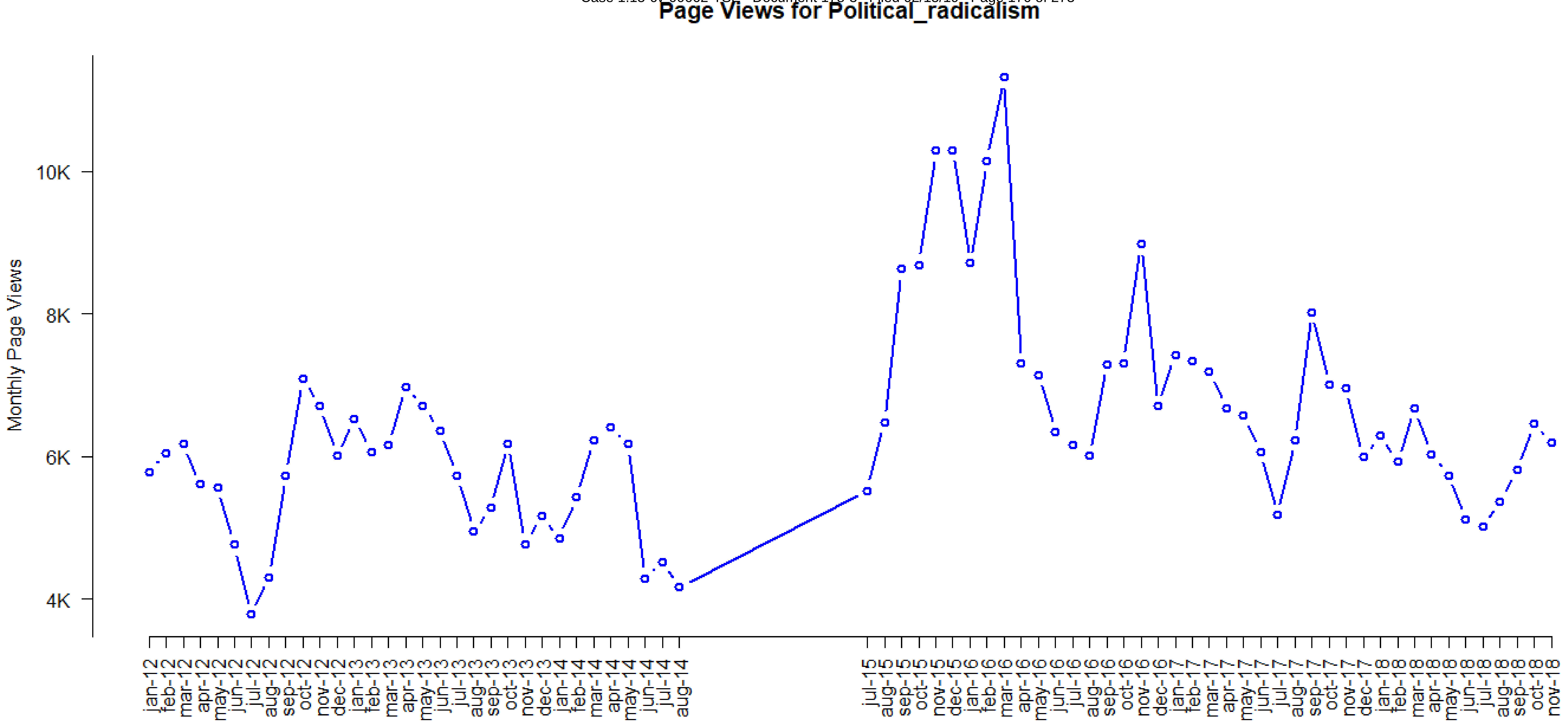


## Page Views for Pirates



## Page Views for PLO




Page Views for Political_radicalism
Monthly Page Views
10K
8K
6K
4K
jan-12
feb-12
mar-12
apr-12
may-12
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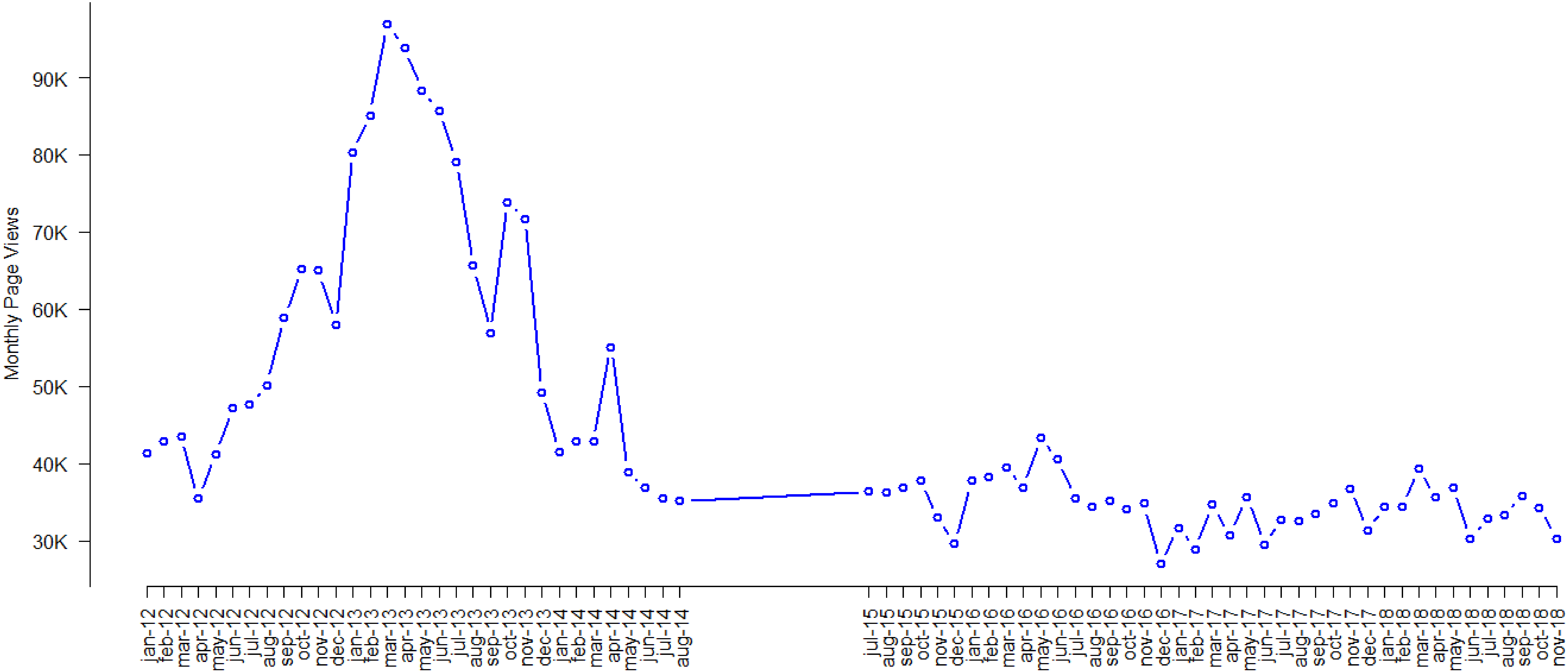
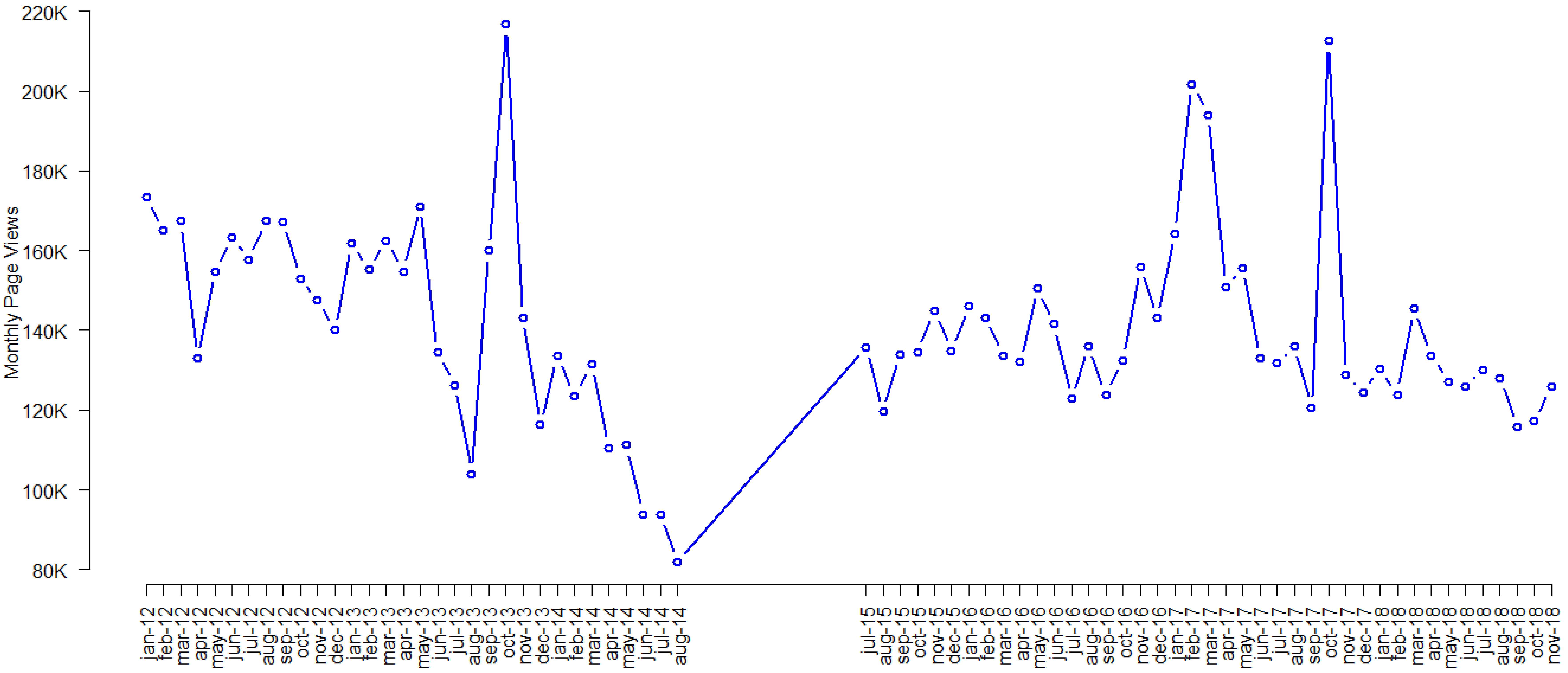
may-17
jun-17
jul-17
aug-17
sep-17
oct-17
nov-17
dec-17
jan-18
feb-18
mar-18
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18

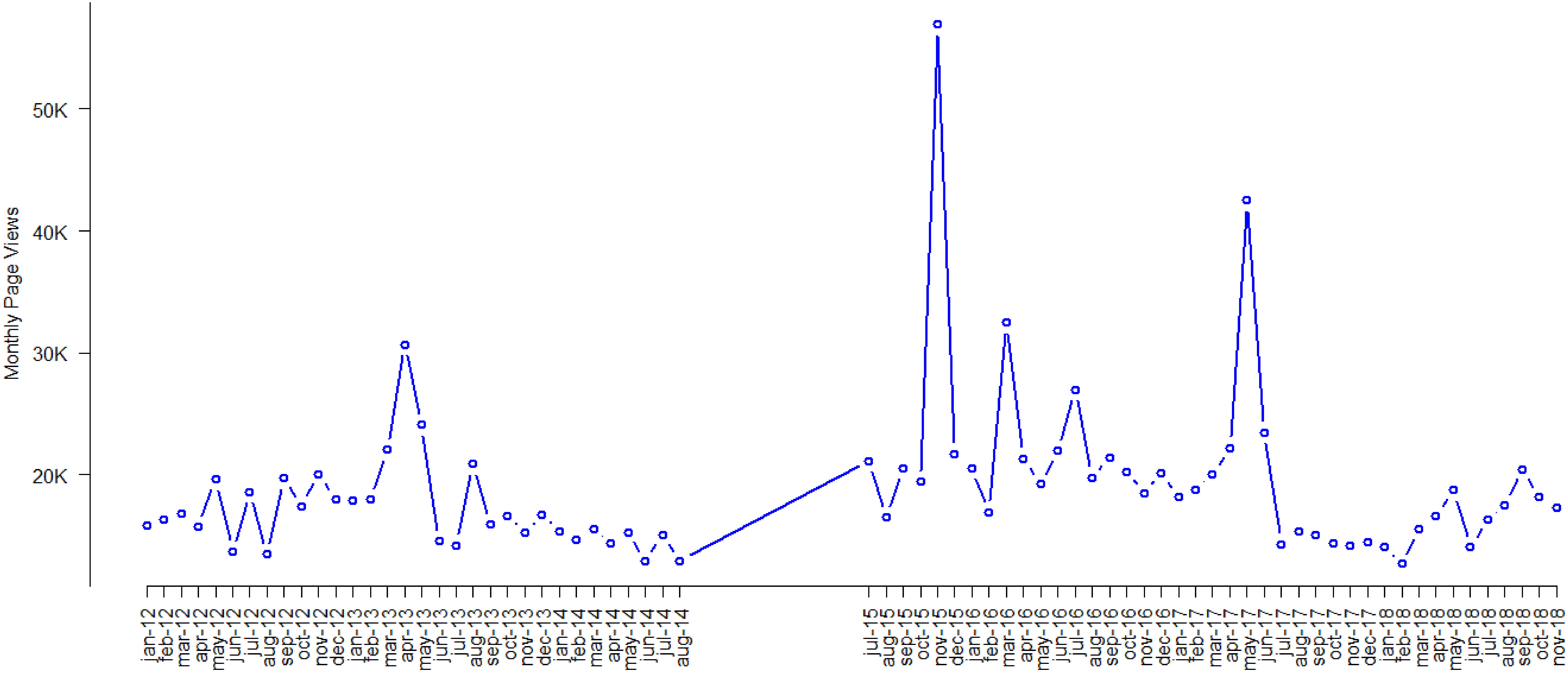
# Page Views for Recruitment

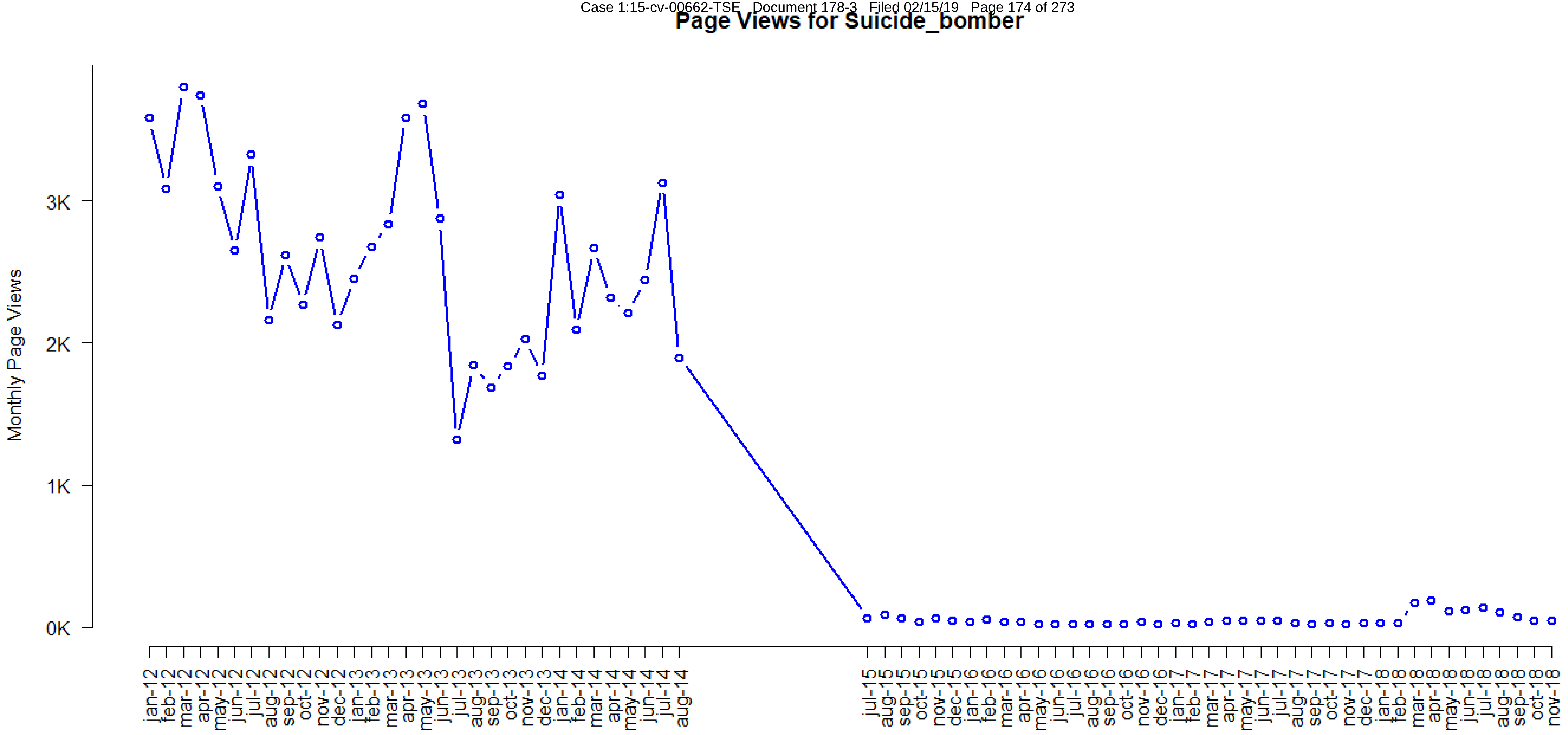


# Page Views for Somalia

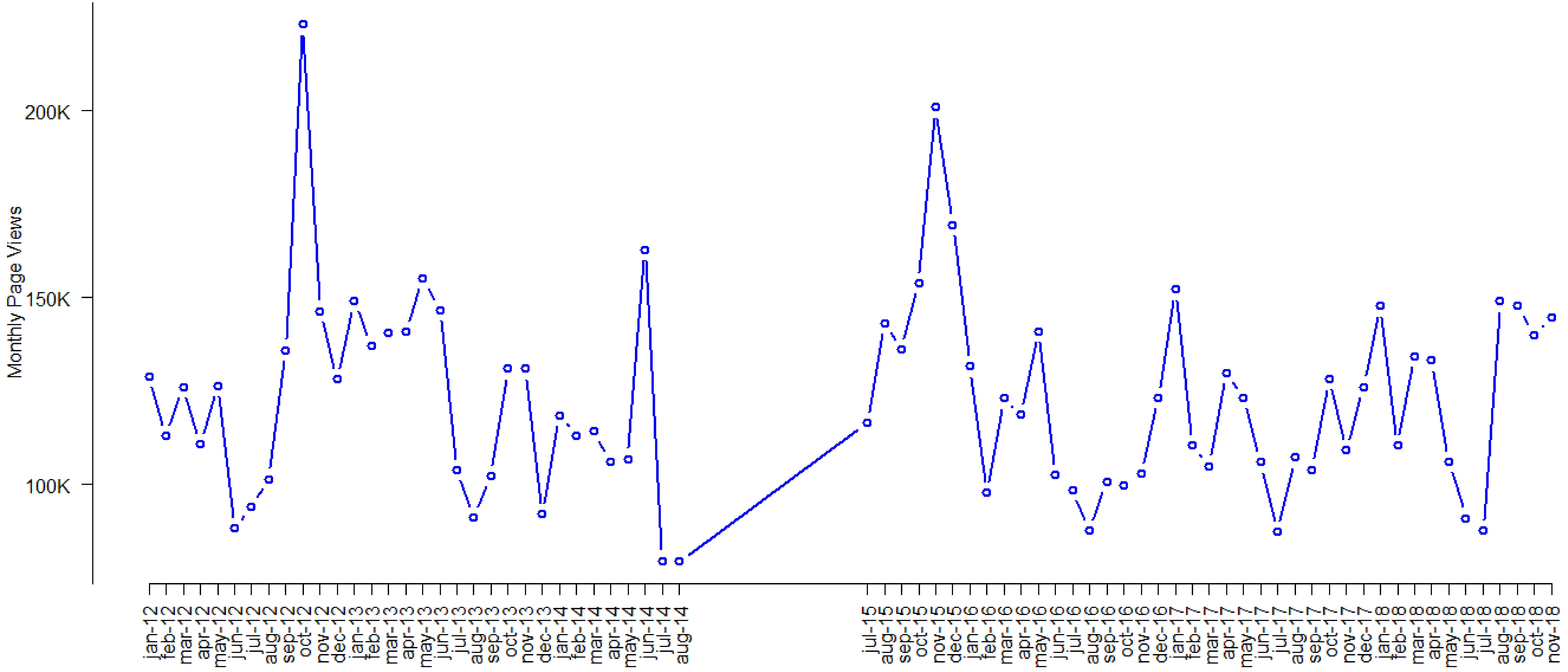


## Page Views for Suicide_attack

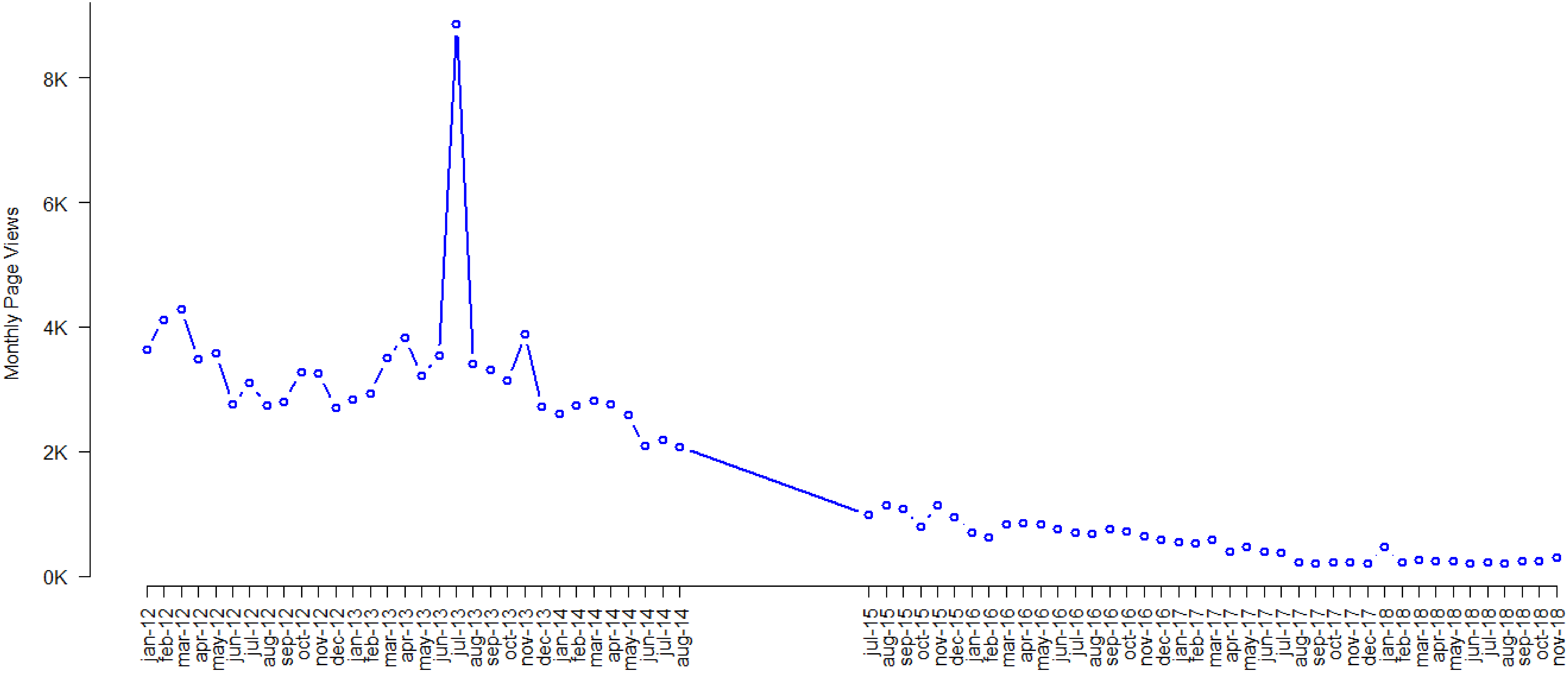


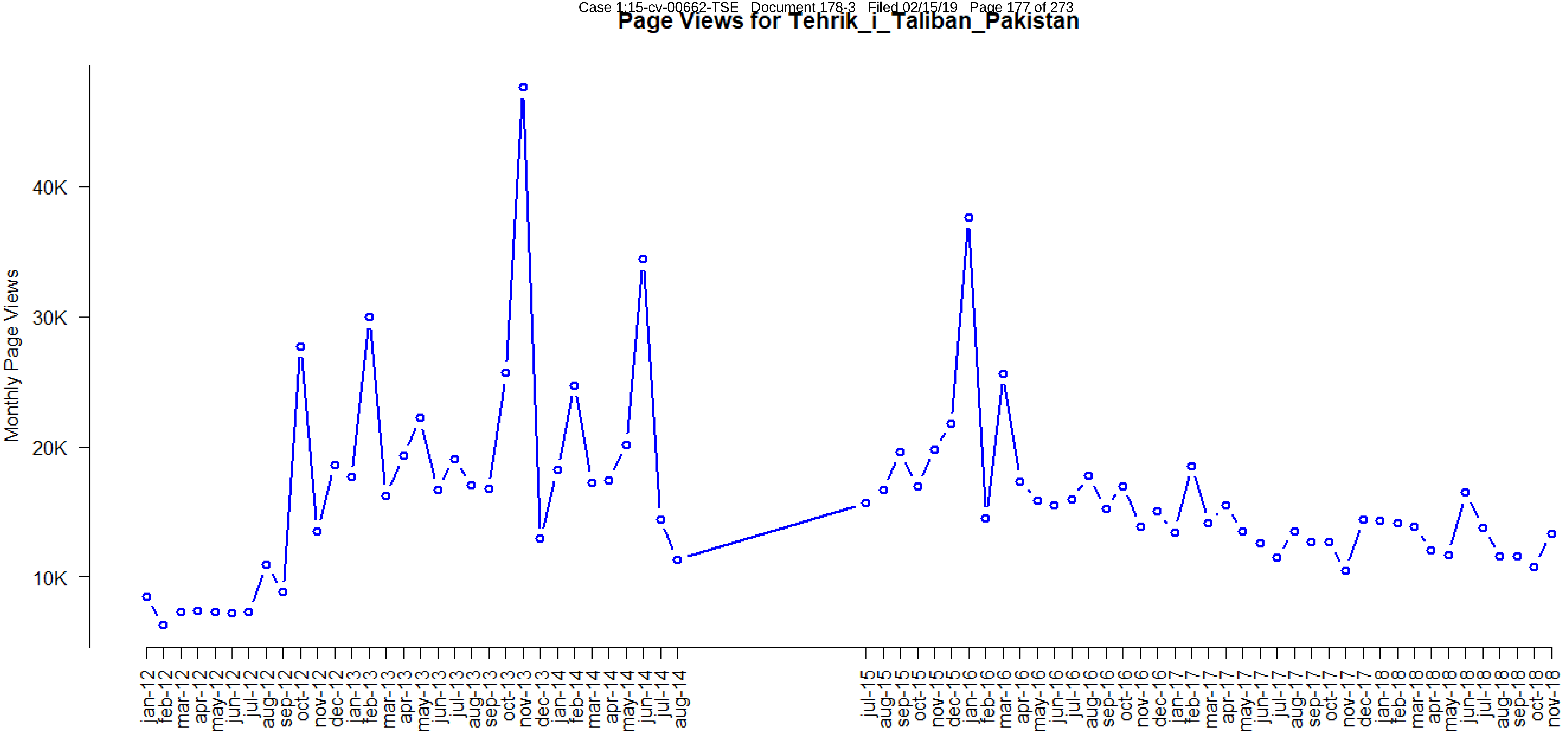

Page Views for Suicide_bomber
Monthly Page Views
3K
2K
1K
0K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14
jul-15
aug-15
sep-15
oct-15
nov-15
dec-15
jan-16
feb-16
mar-16
apr-16
may-16
jun-16
jul-16
aug-16
sep-16
oct-16
nov-16
dec-16
jan-17
feb-17
mar-17
apr-17
may-17
jun-17
jul-17
aug-17
sep-17
oct-17
nov-17
dec-17
jan-18
feb-18
mar-18
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18

# Page Views for Taliban

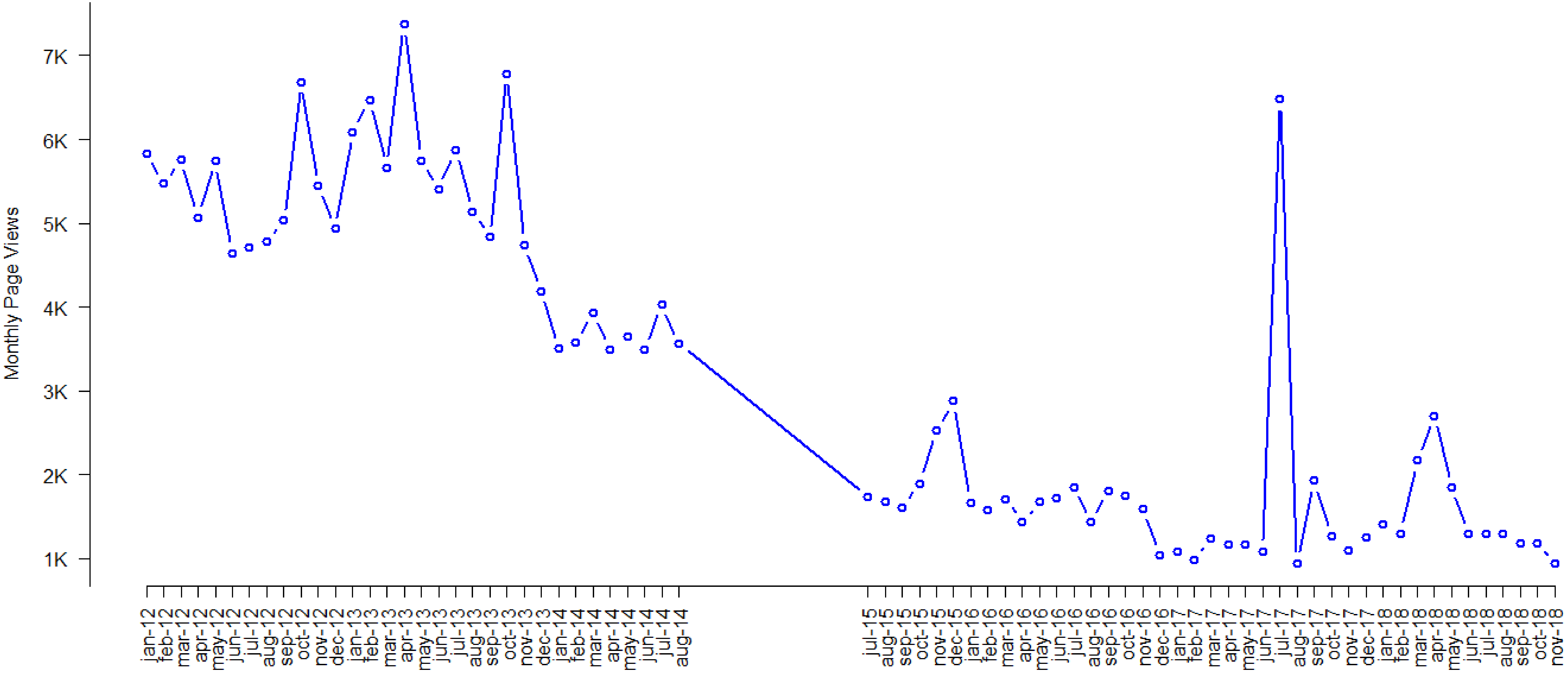


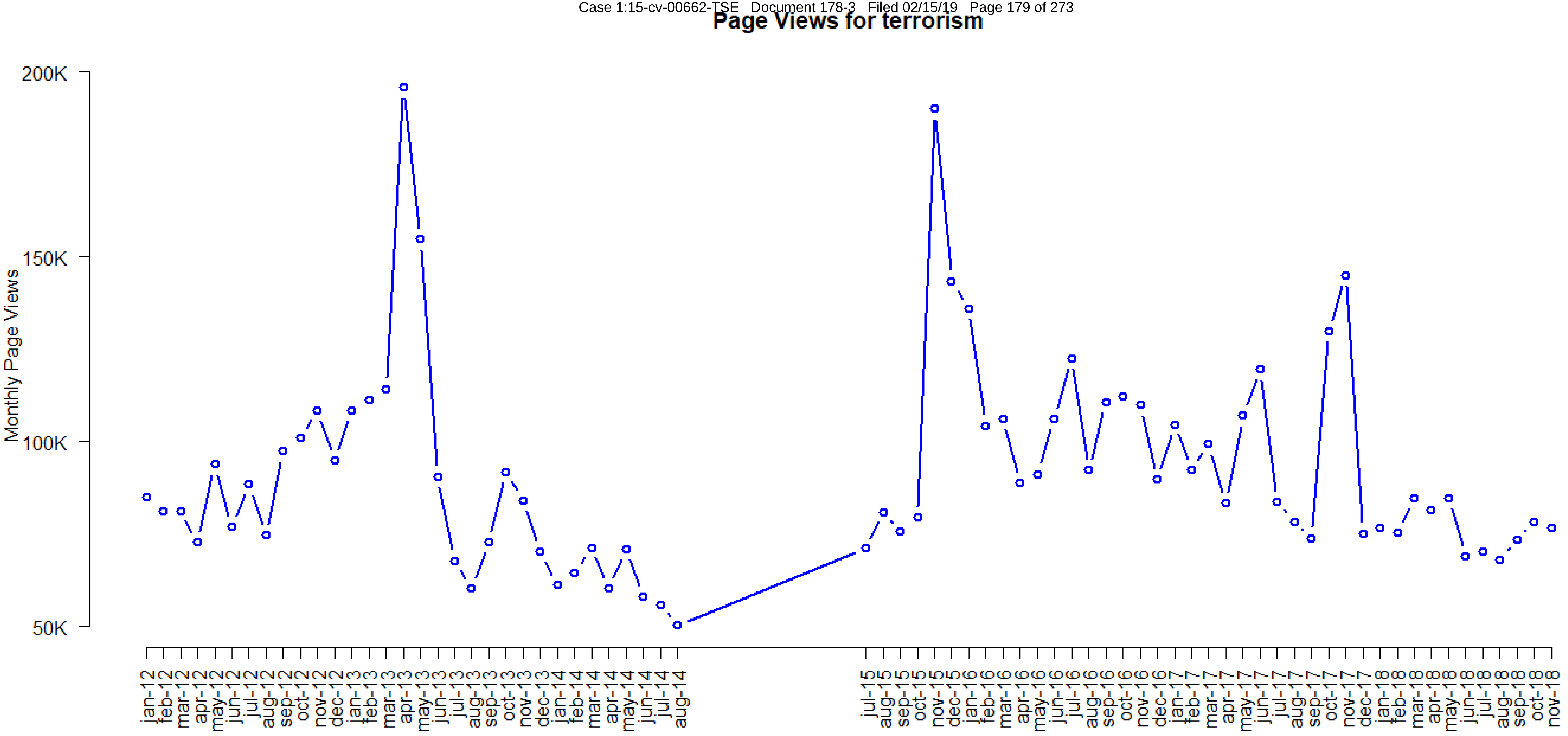
## Page Views for Tamil_Tigers



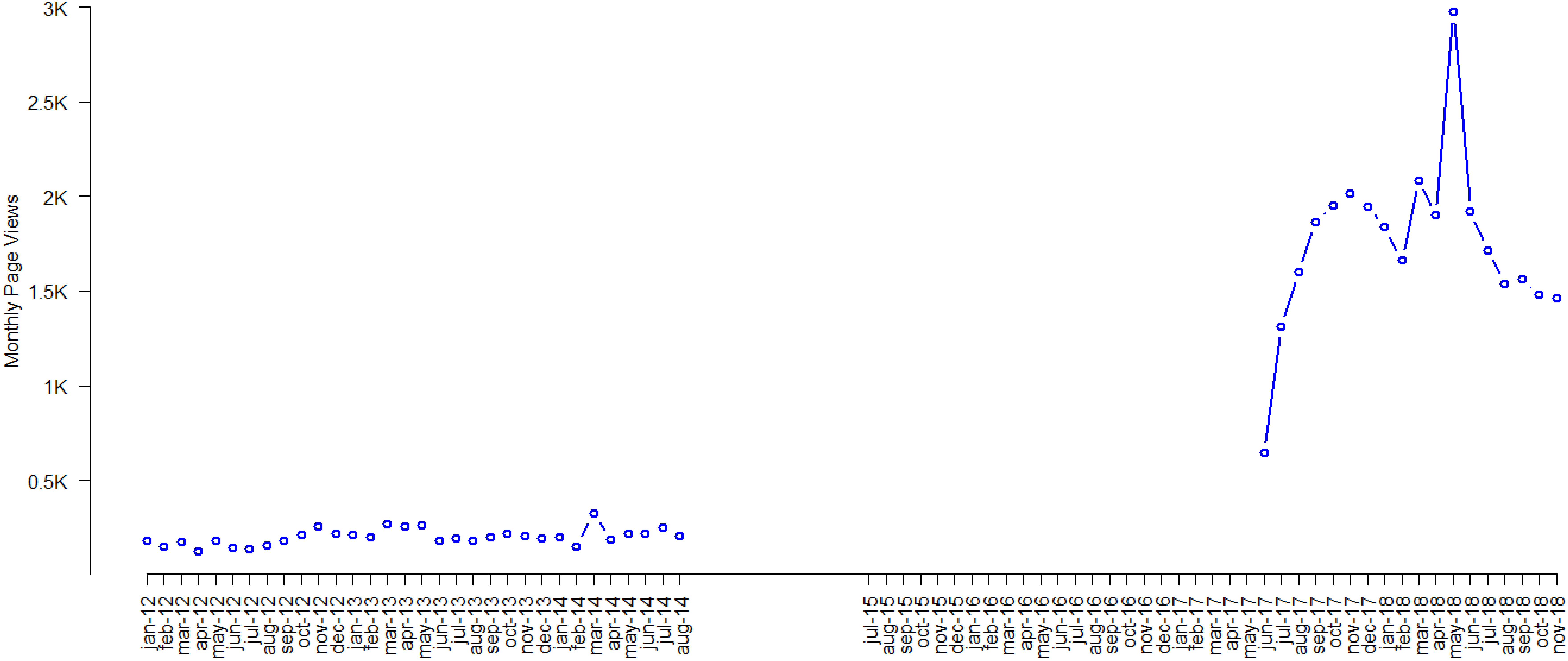

Page Views for Tehrik_i_Taliban_Pakistan
Monthly Page Views
10K
20K
30K
40K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14
jul-15
aug-15
sep-15
oct-15
nov-15
dec-15
jan-16
feb-16
mar-16
apr-16
may-16
jun-16
jul-16
aug-16
sep-16
oct-16
nov-16
dec-16
jan-17
feb-17
mar-17
apr-17
may-17
jun-17
jul-17
aug-17
sep-17
oct-17
nov-17
dec-17
jan-18
feb-18
mar-18
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18

# Page Views for terror

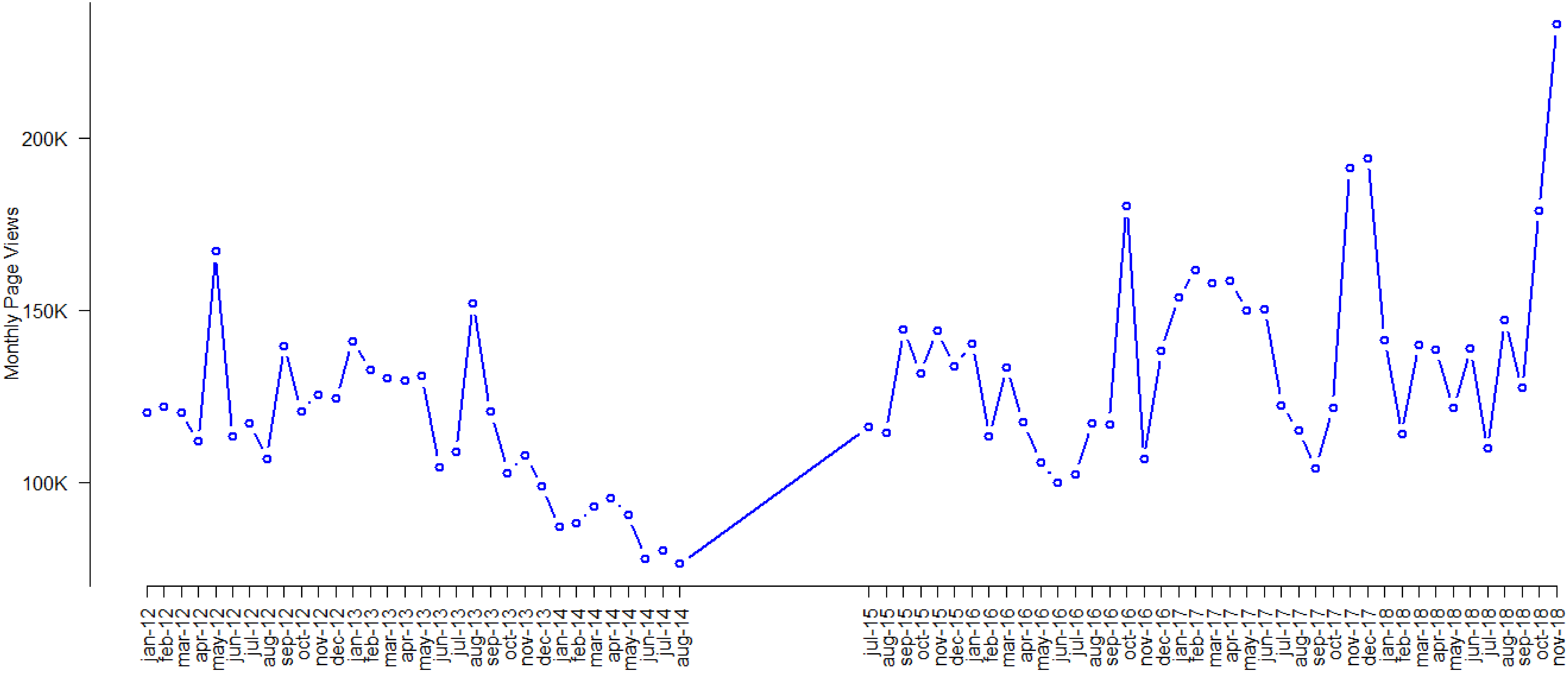



Page Views for terrorism
Monthly Page Views
200K
150K
100K
50K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14
jul-15
aug-15
sep-15
oct-15
nov-15
dec-15
jan-16
feb-16
mar-16
apr-16
may-16
jun-16
jul-16
aug-16
sep-16
oct-16
nov-16
dec-16
jan-17
feb-17
mar-17
apr-17
may-17
jun-17
jul-17
aug-17
sep-17
oct-17
nov-17
dec-17
jan-18
feb-18
mar-18
apr-18
may-18
jun-18
jul-18
aug-18
sep-18
oct-18
nov-18

## Page Views for Weapons_grade

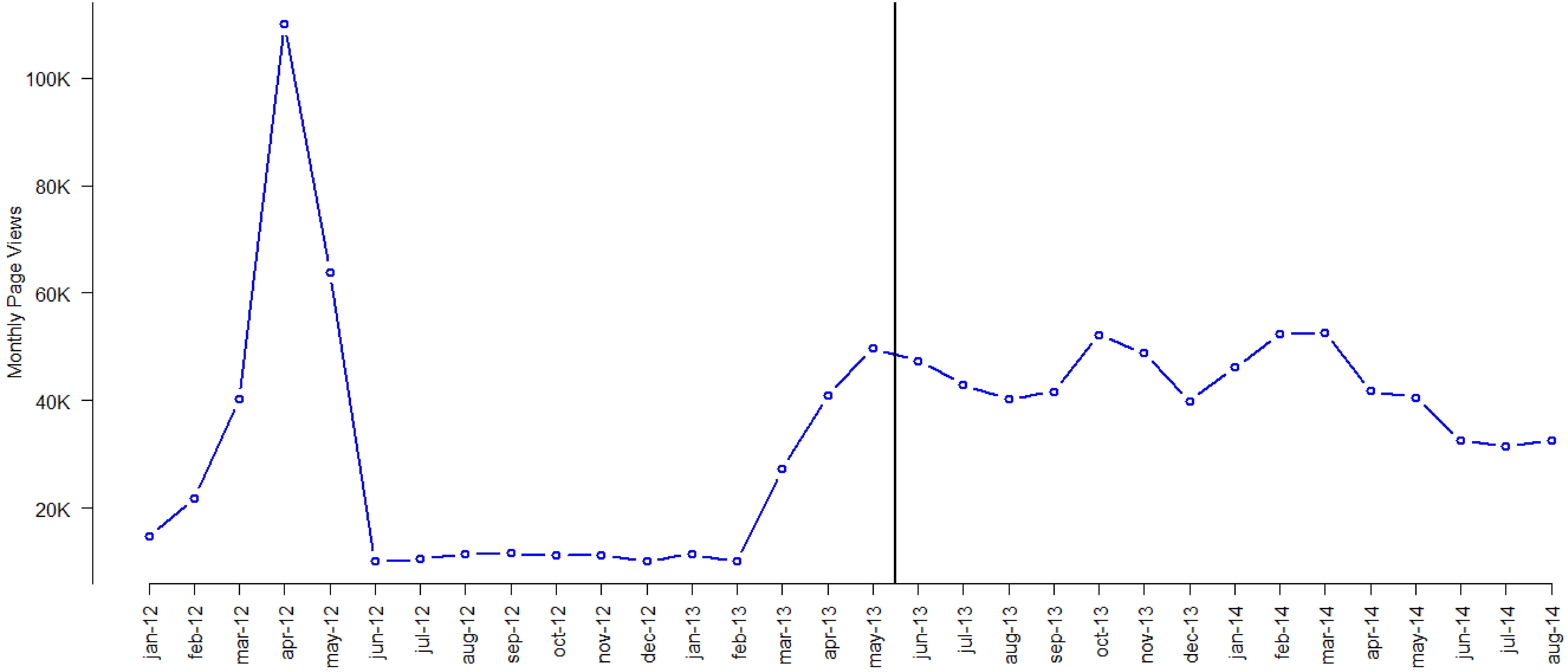


# Page Views for Yemen

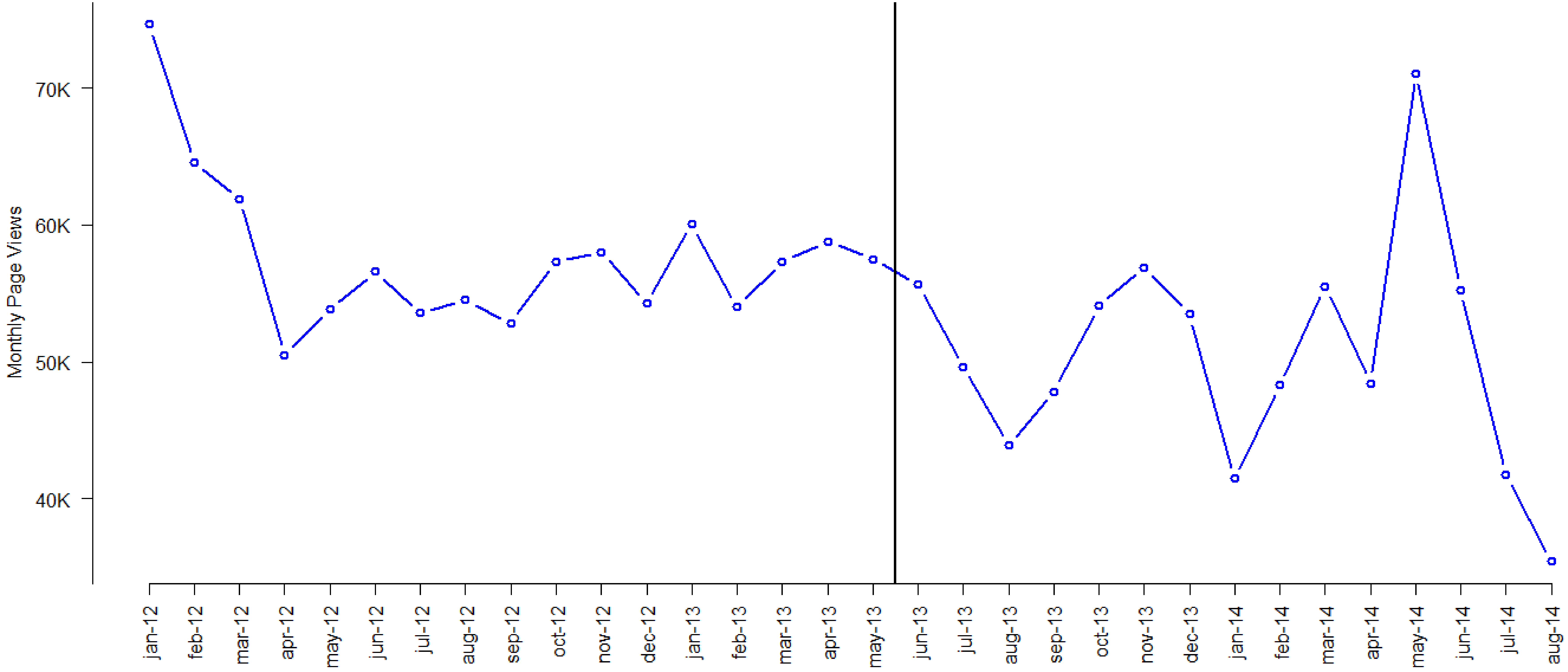


# APPENDIX VI: Page Views for 85 Comparative Articles

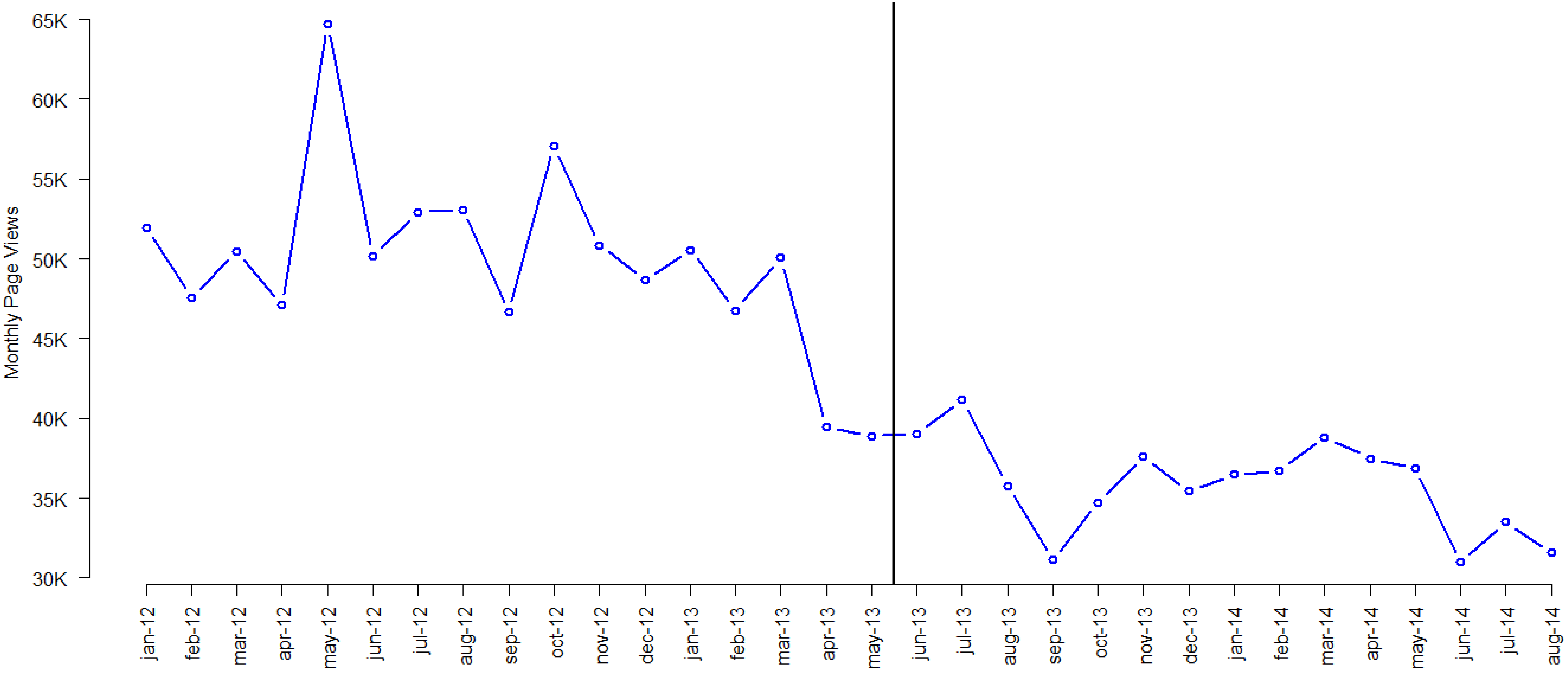
## Infrastructure: Page Views for airplane

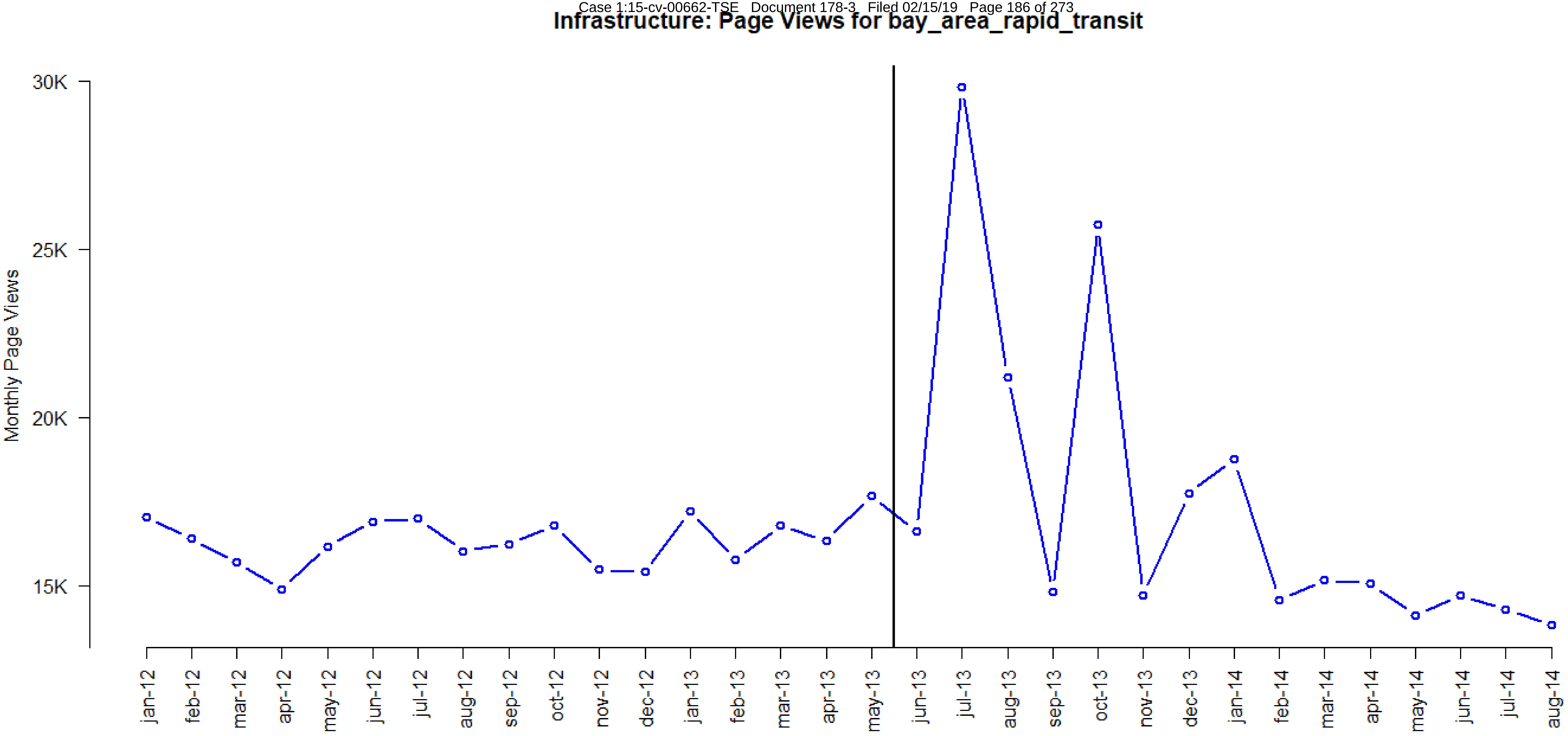


# Infrastructure: Page Views for airport

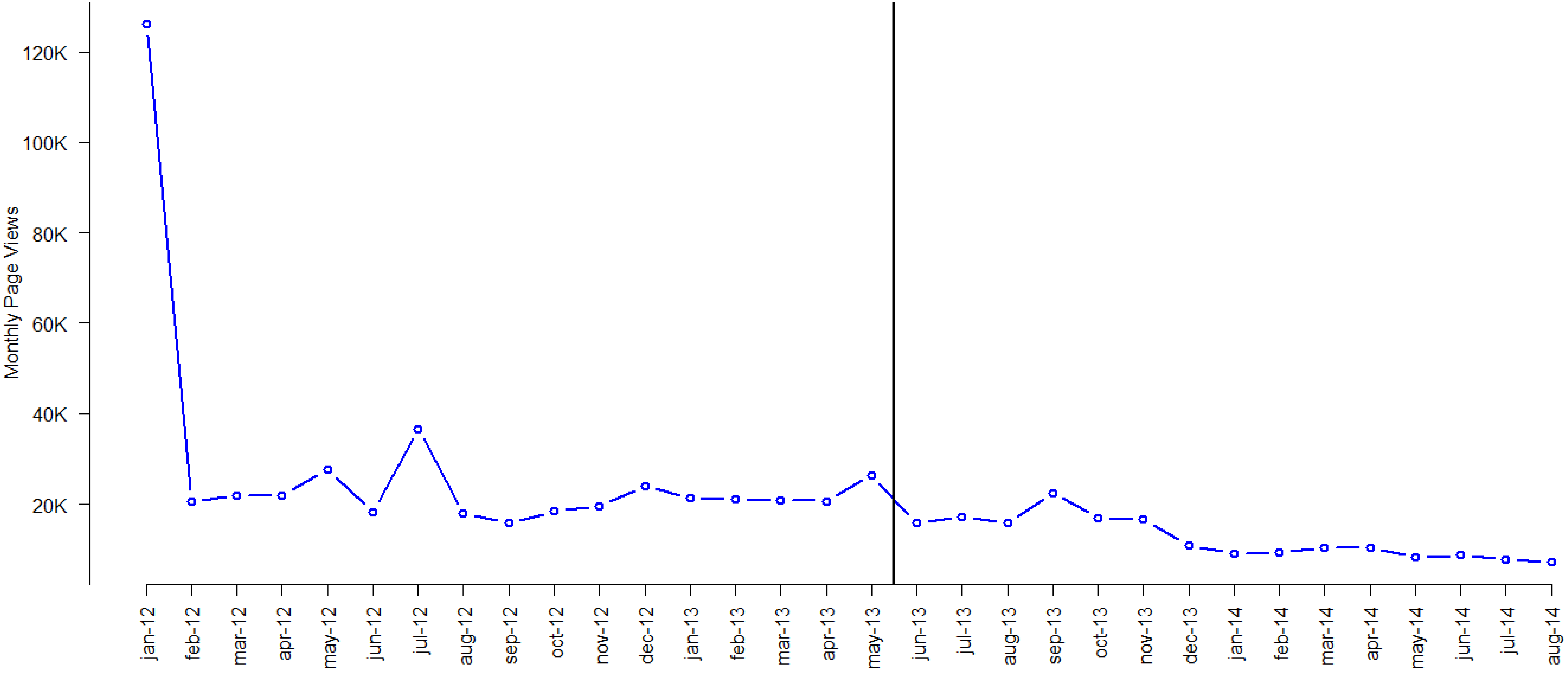


# Infrastructure: Page Views for amtrak

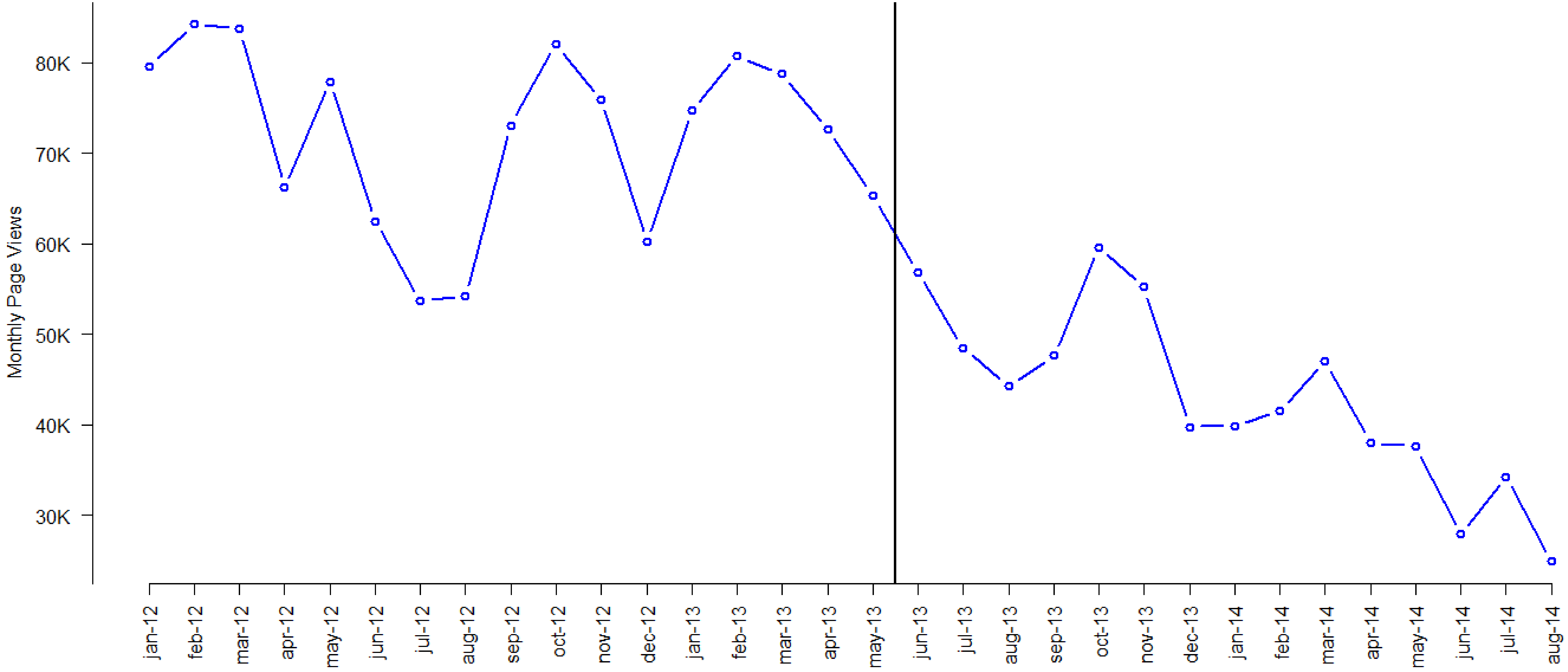



Infrastructure: Page Views for bay_area_rapid_transit
Monthly Page Views
30K
25K
20K
15K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

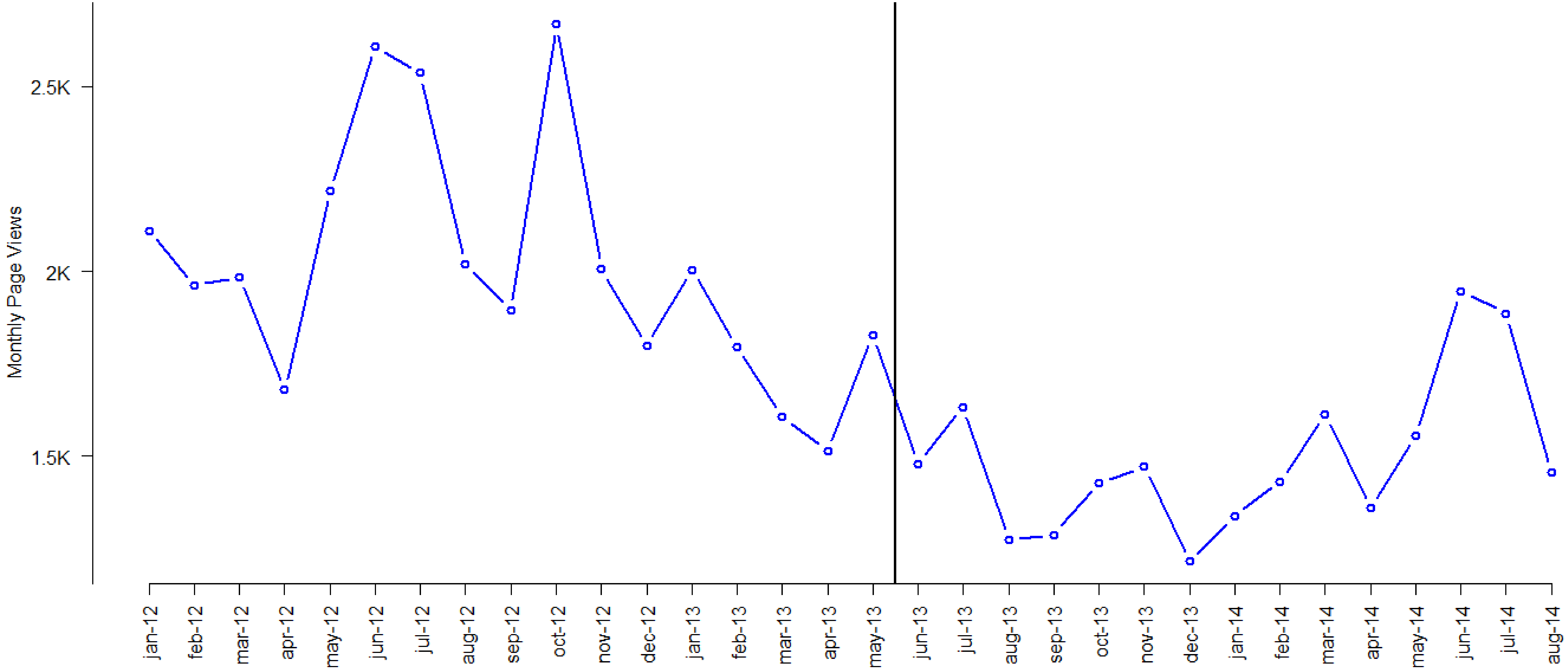
# Infrastructure: Page Views for blackout



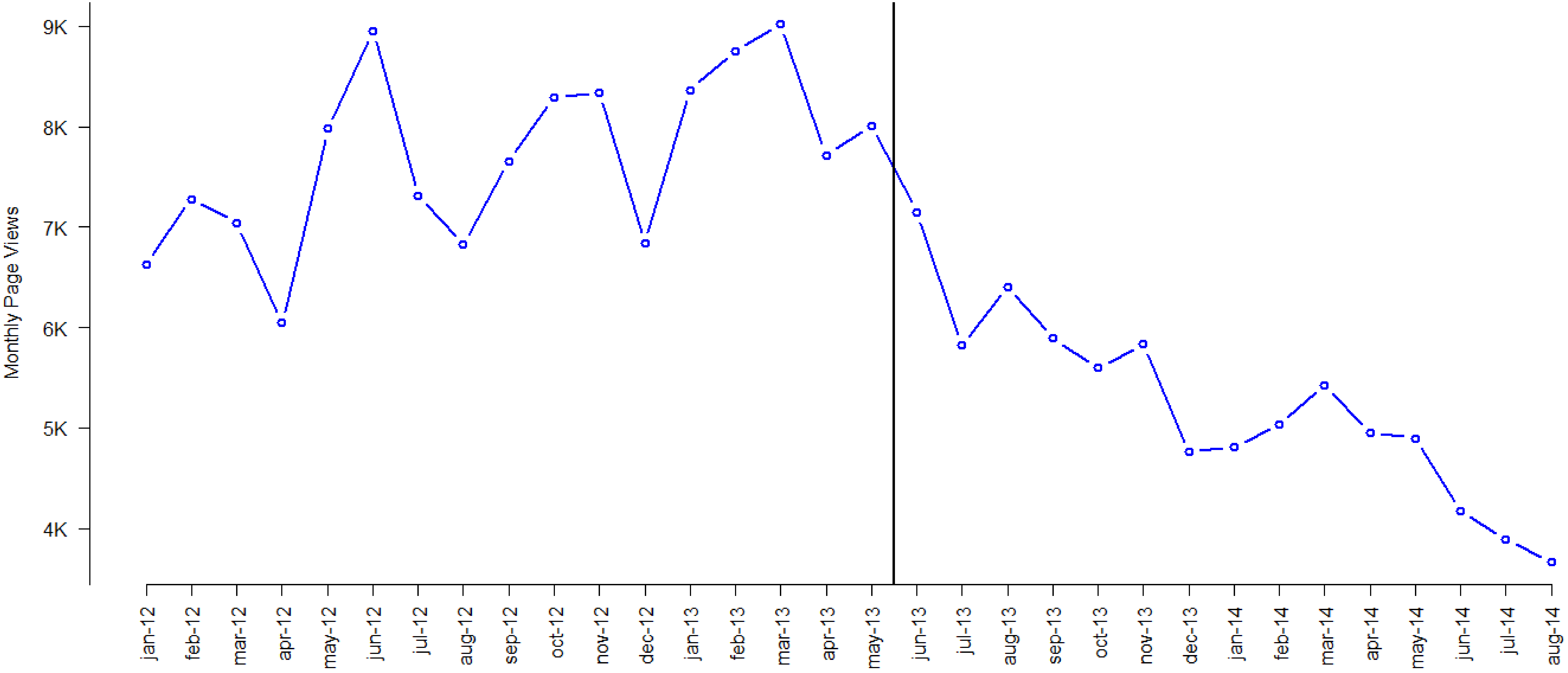
# Infrastructure: Page Views for bridge



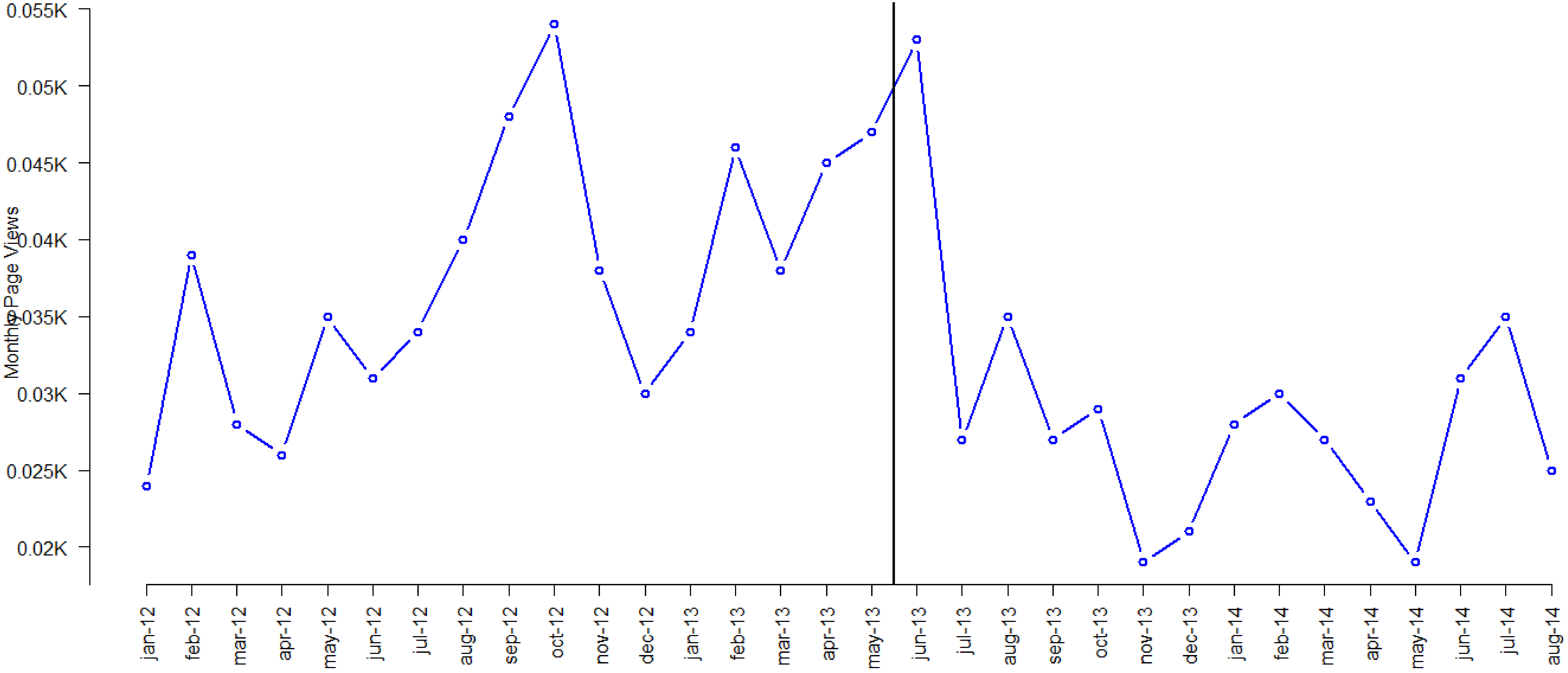
## Infrastructure: Page Views for brownout



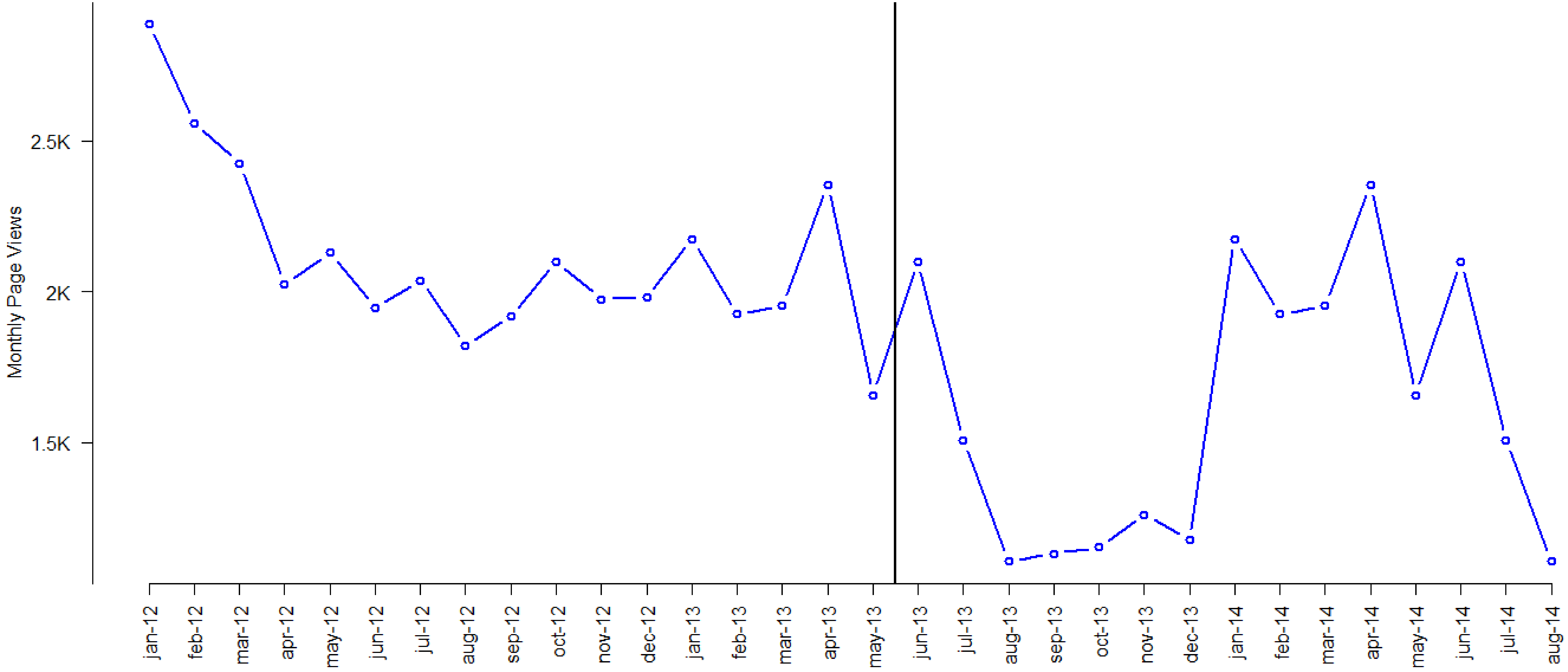
# Infrastructure: Page Views for chemical_burn



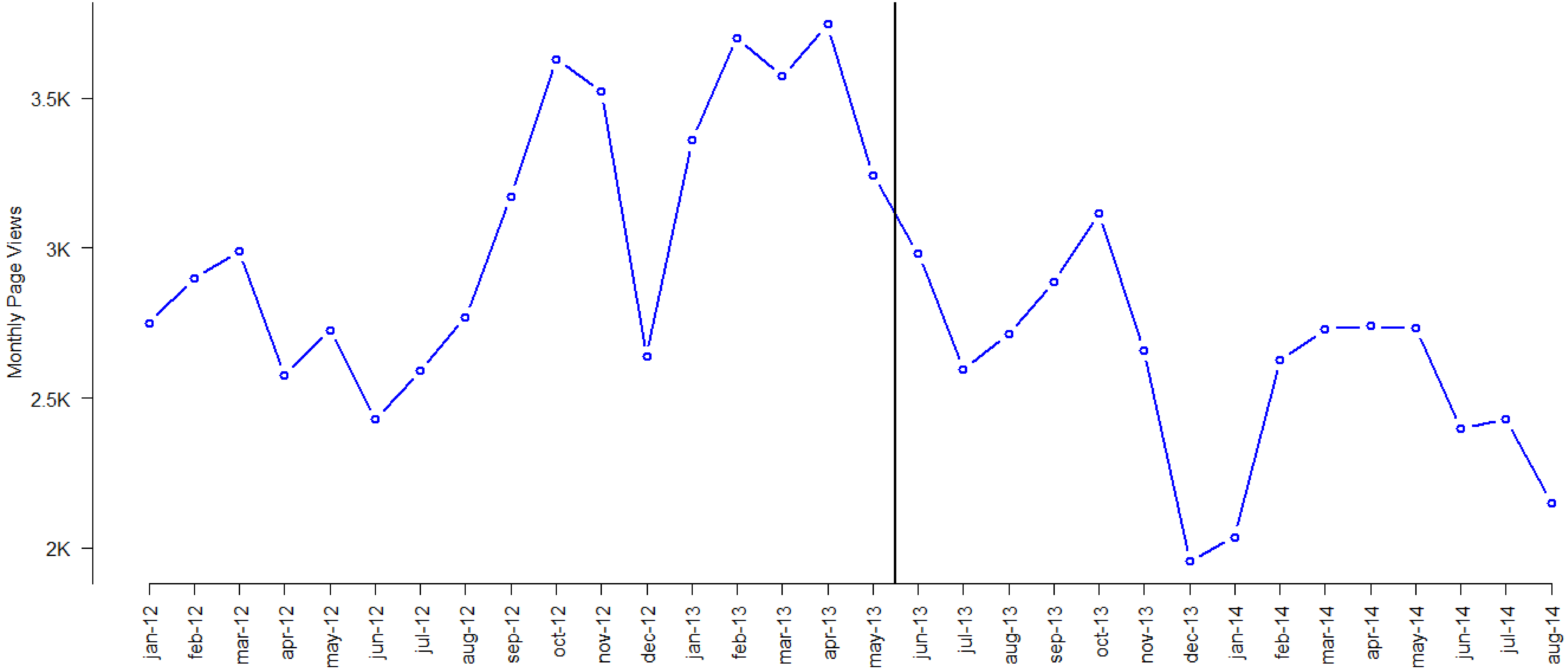
# Infrastructure: Page Views for cikr

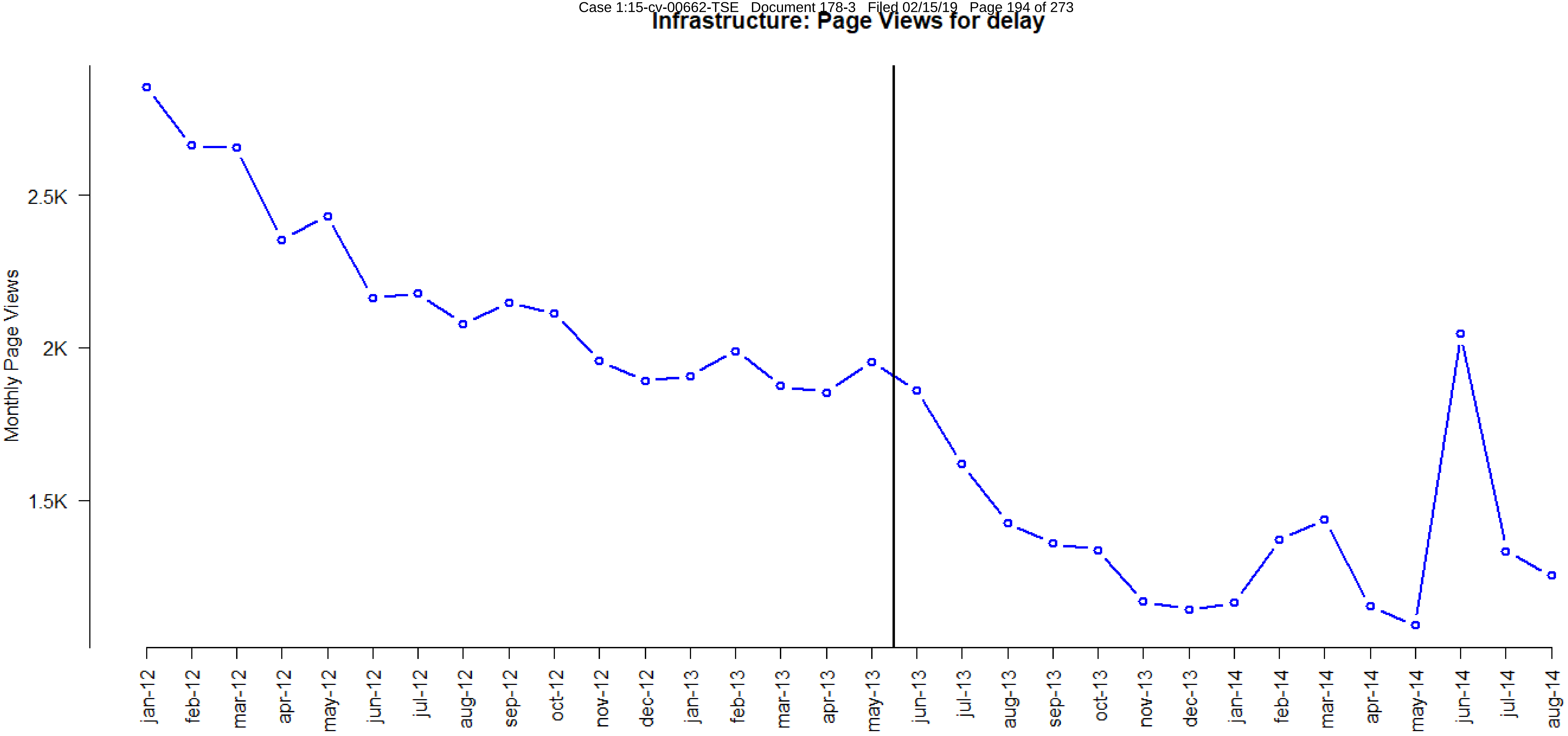


# Infrastructure: Page Views for collapse

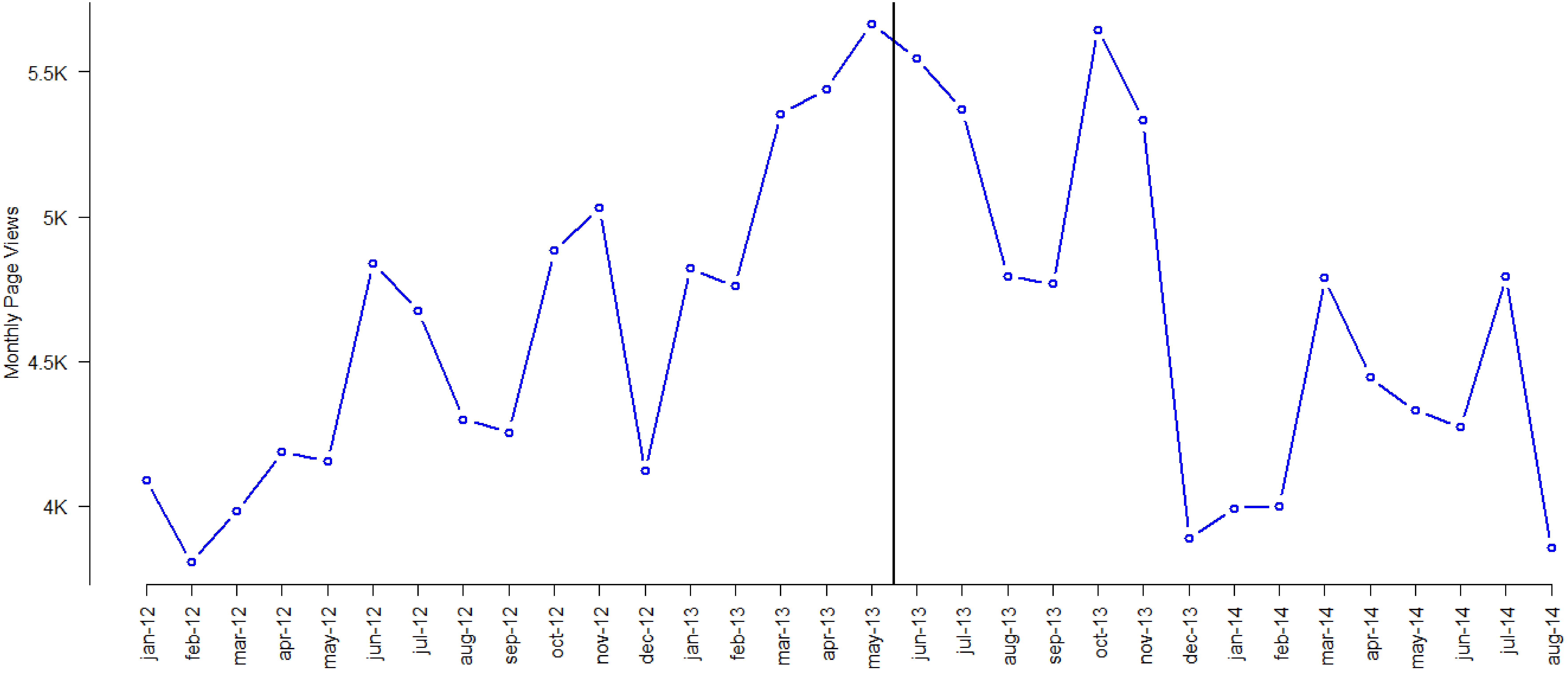


## Infrastructure: Page Views for critical_infrastructure

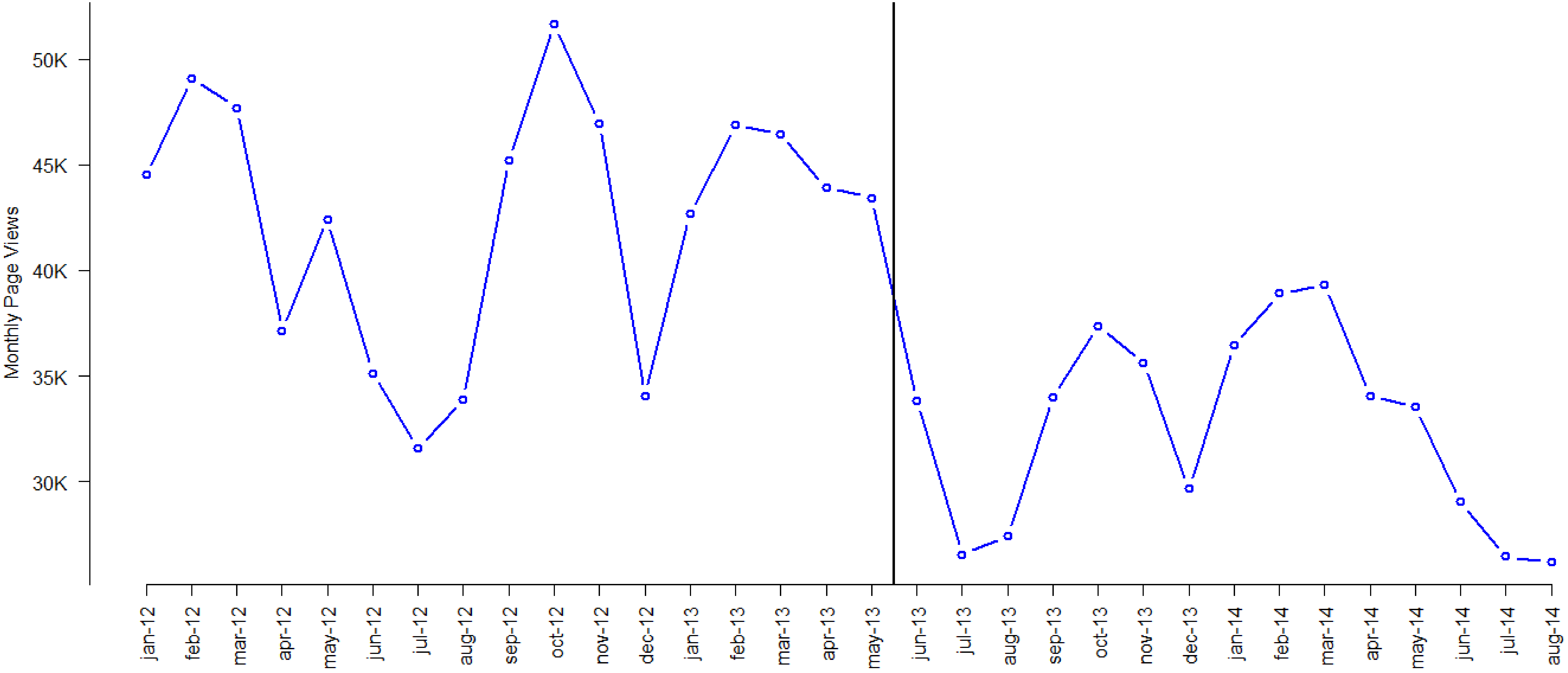



Infrastructure: Page Views for delay
Monthly Page Views
2.5K
2K
1.5K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

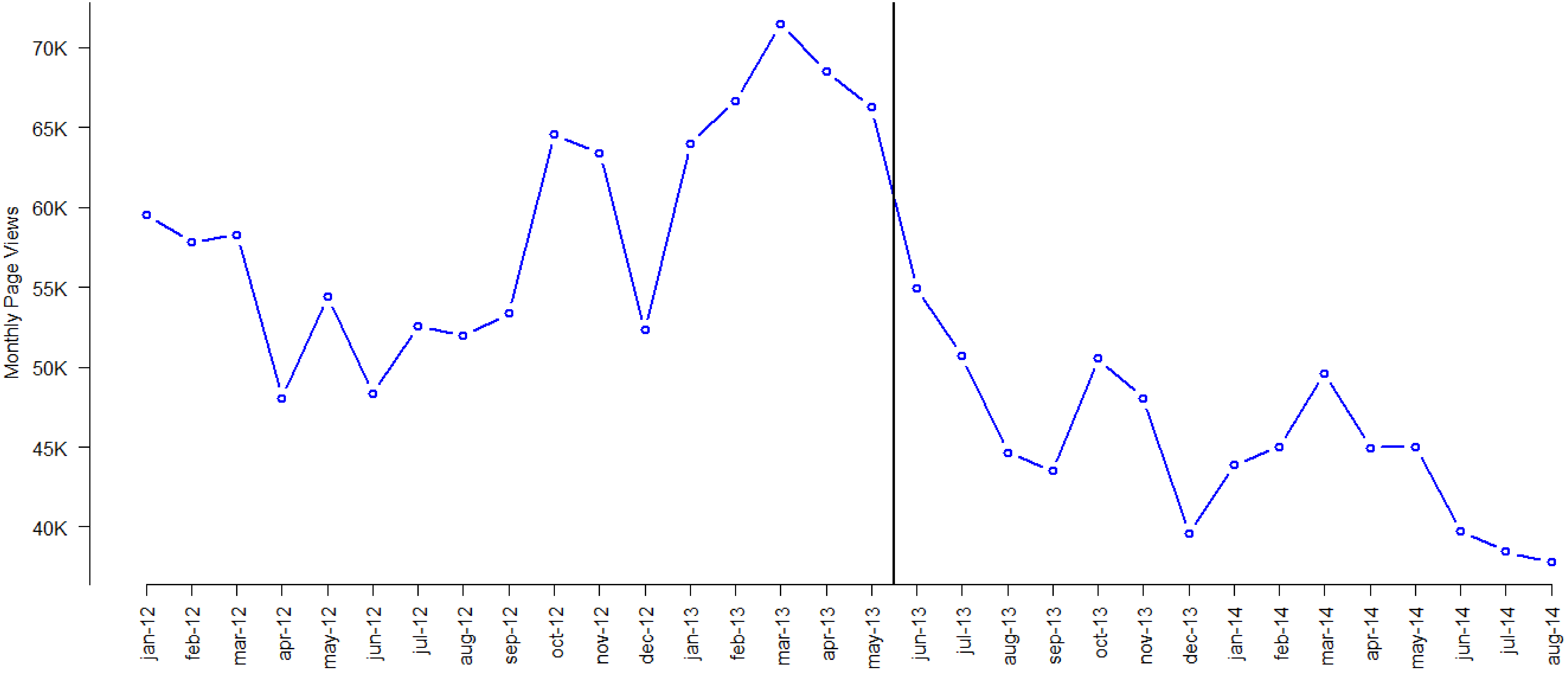
# Infrastructure: Page Views for dock_maritime



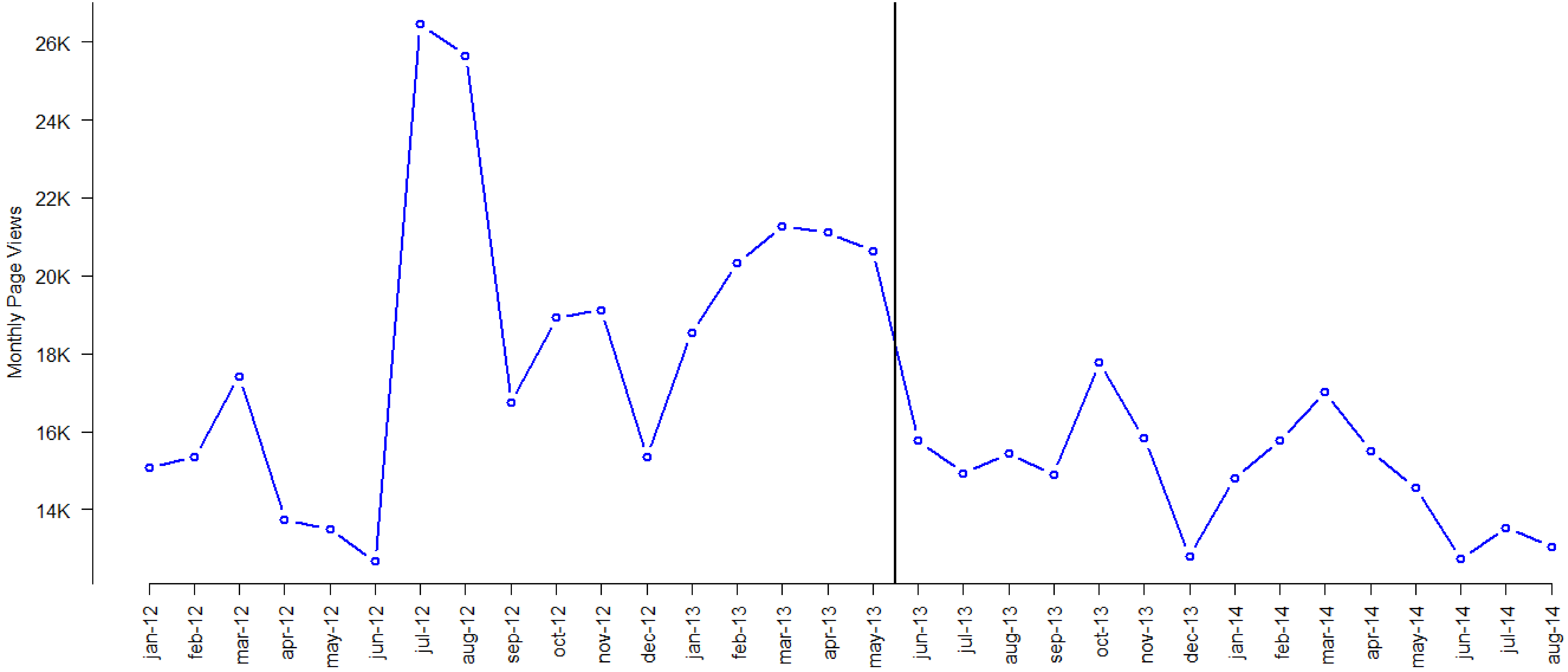
## Infrastructure: Page Views for electric_power



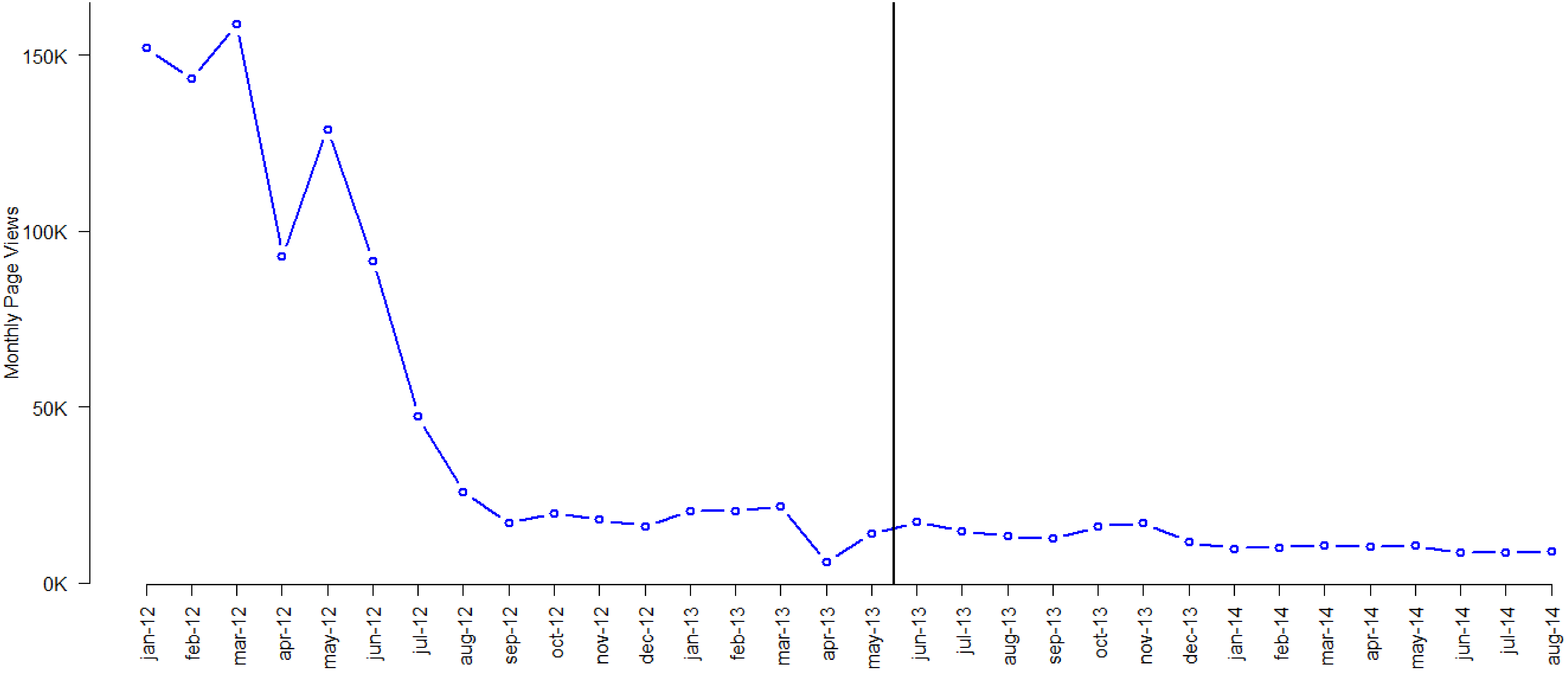
# Infrastructure: Page Views for electric_power_transmission



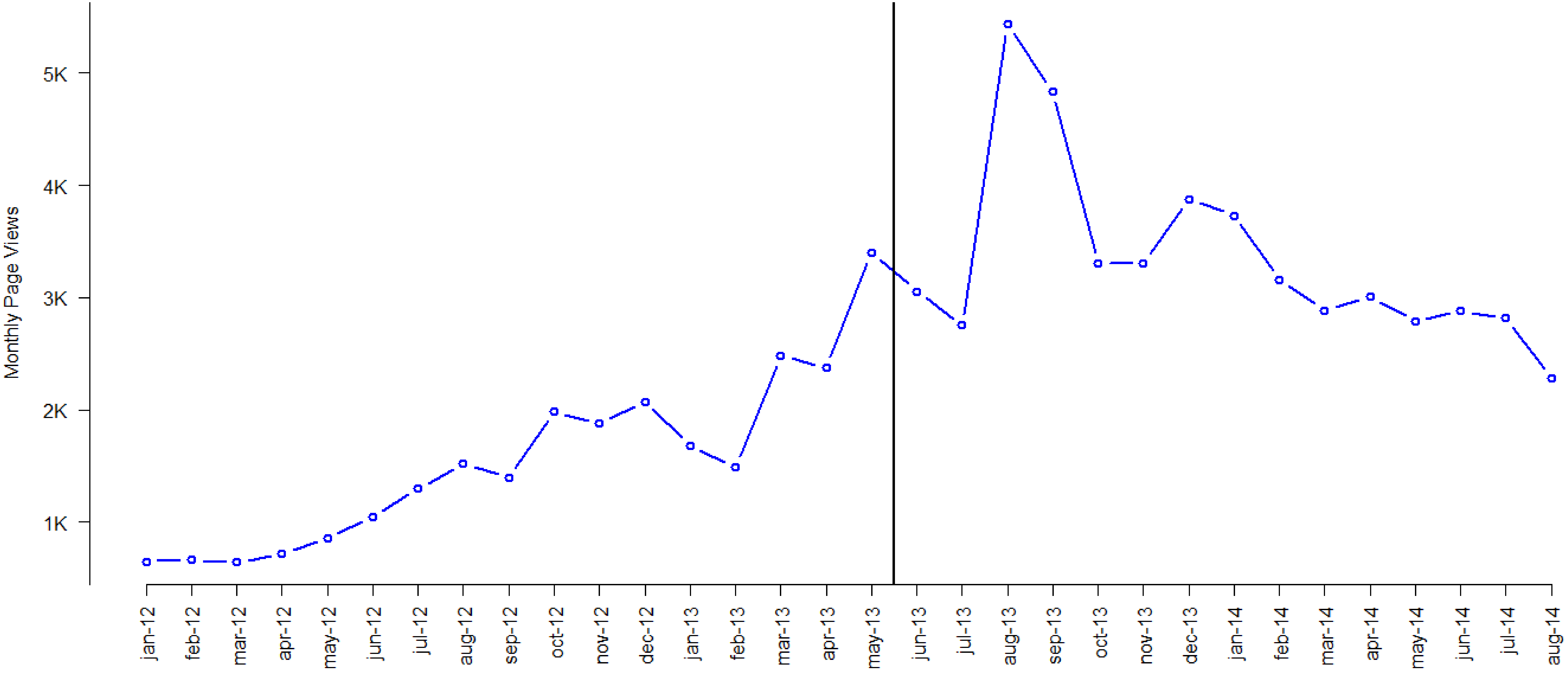
# Infrastructure: Page Views for electrical_grid



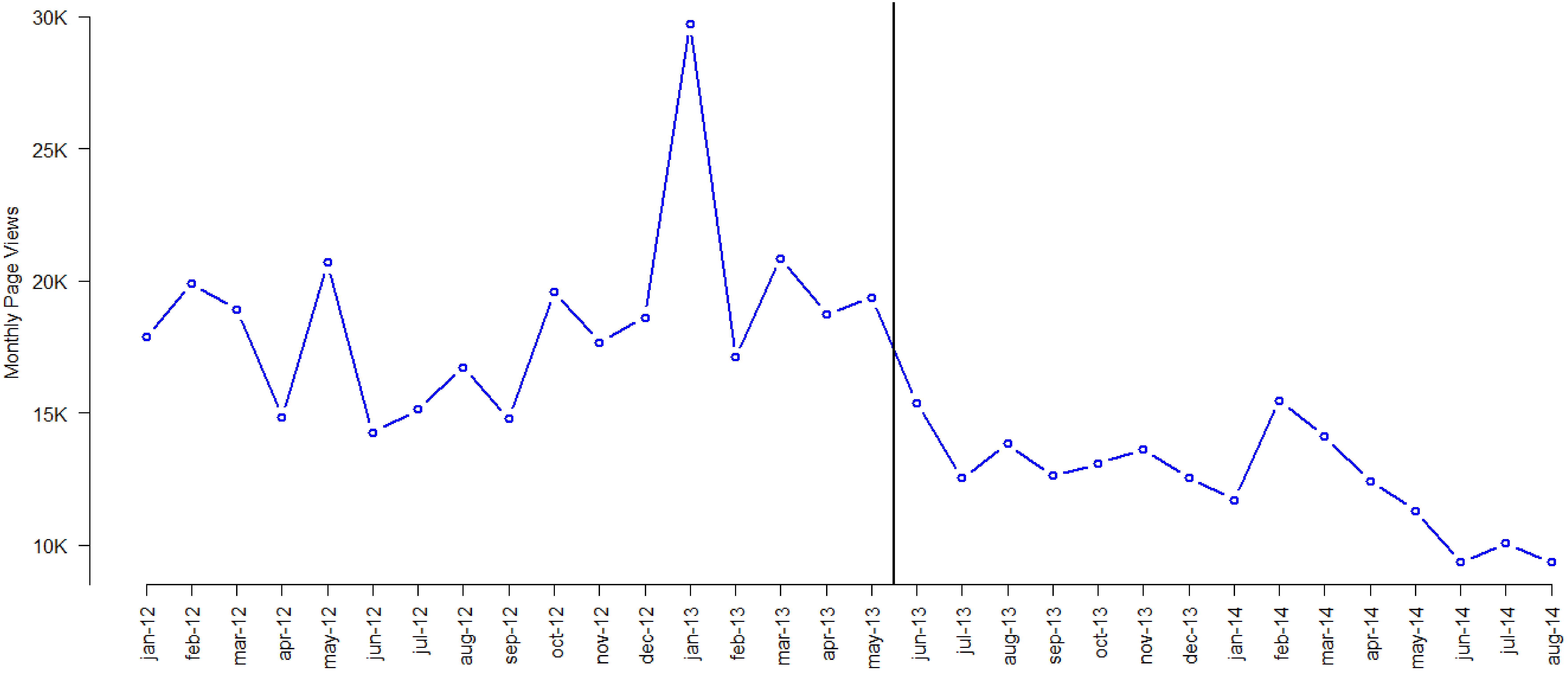
## Infrastructure: Page Views for failure

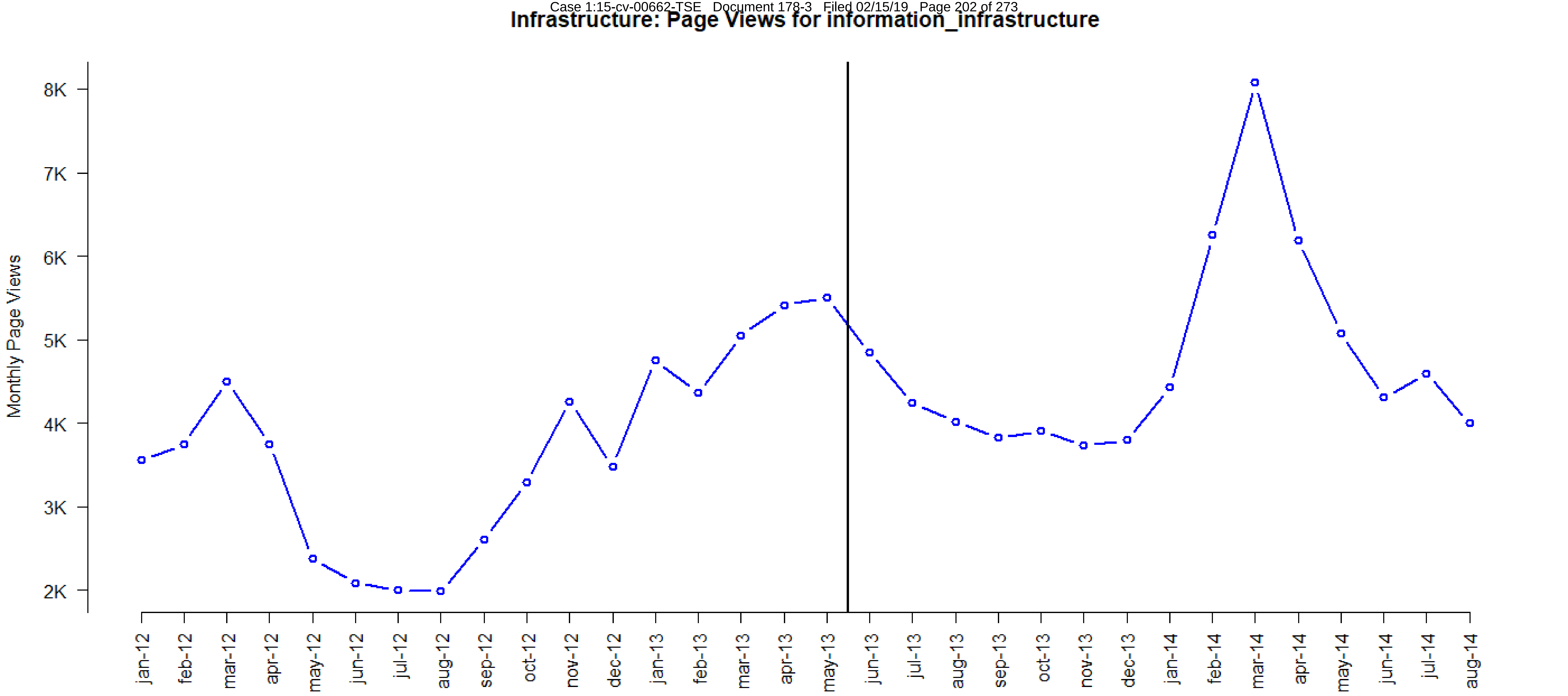


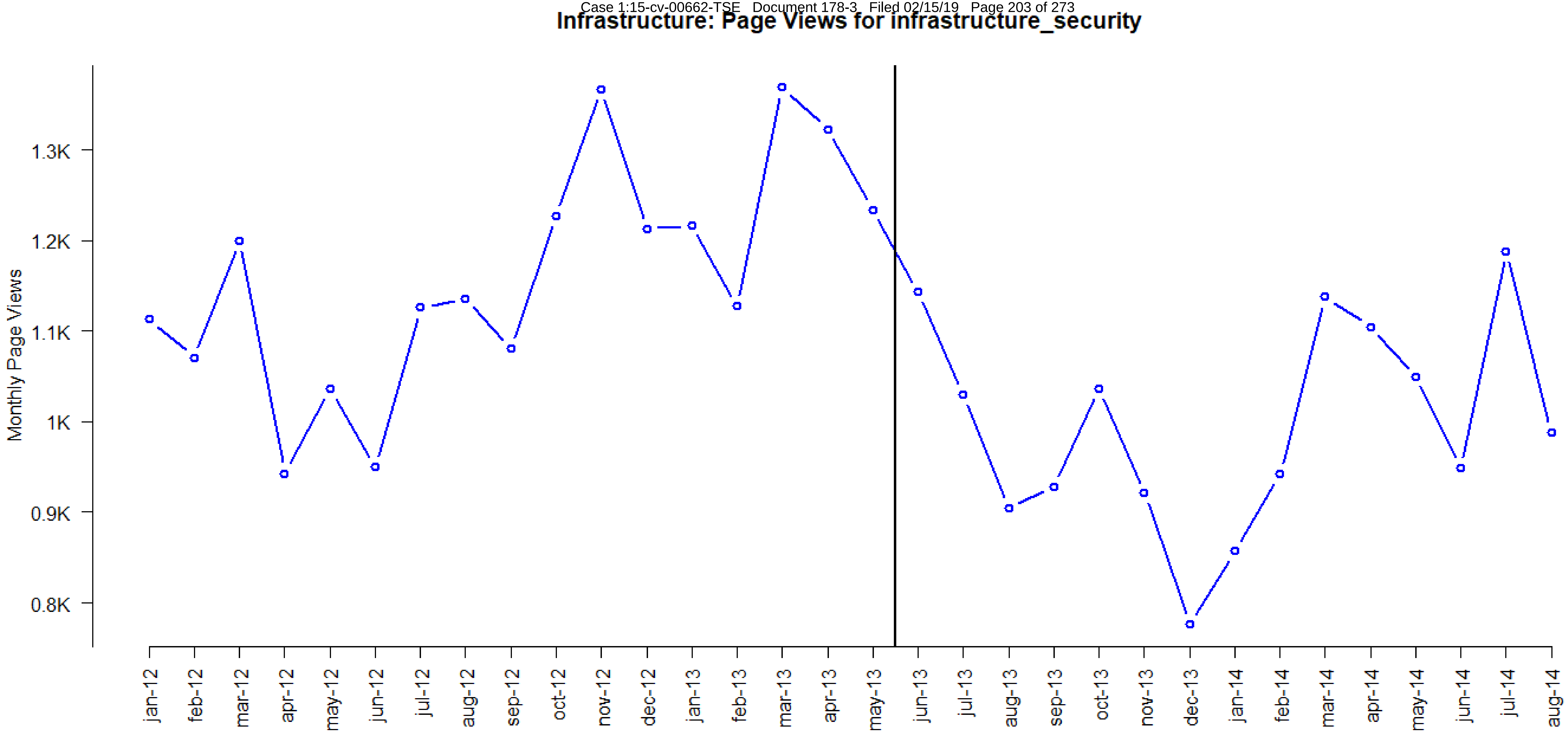
# Infrastructure: Page Views for Flight_cancellation_and_delay



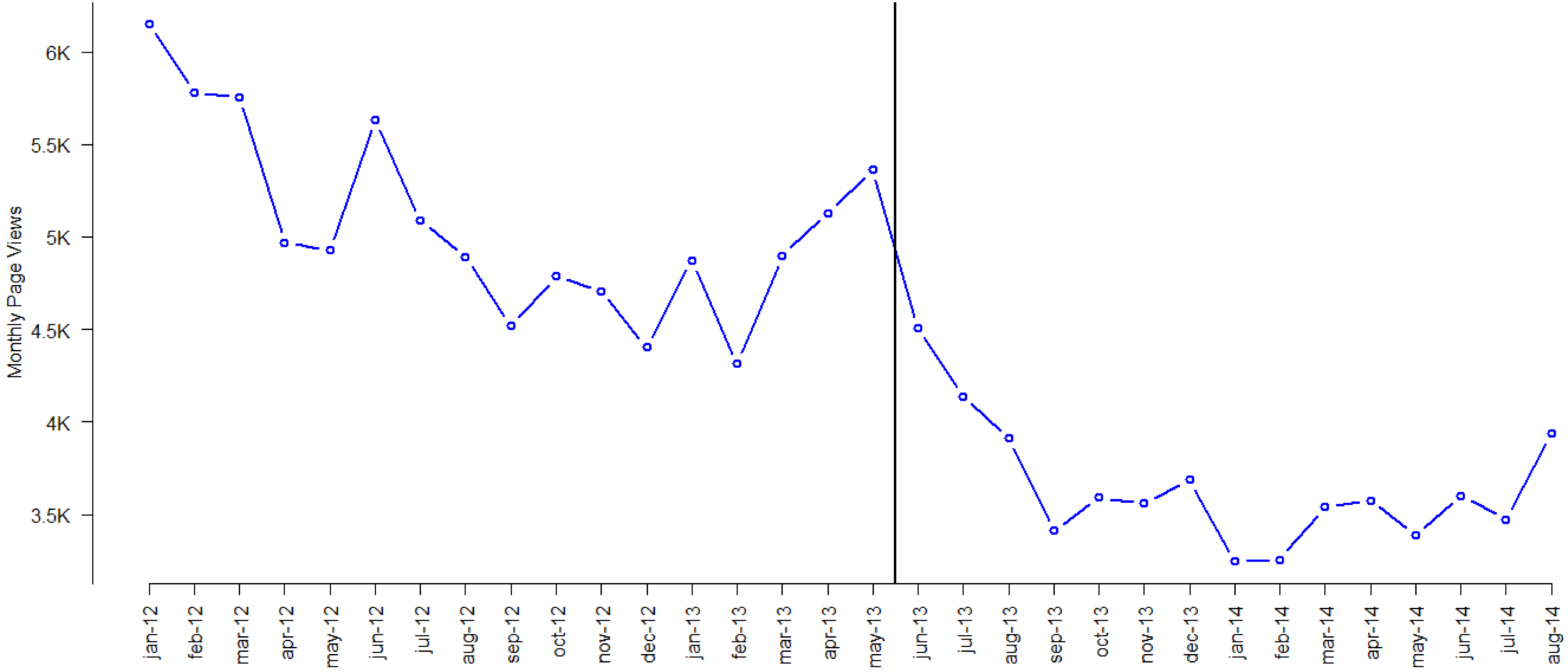
# Infrastructure: Page Views for full_body_scanner



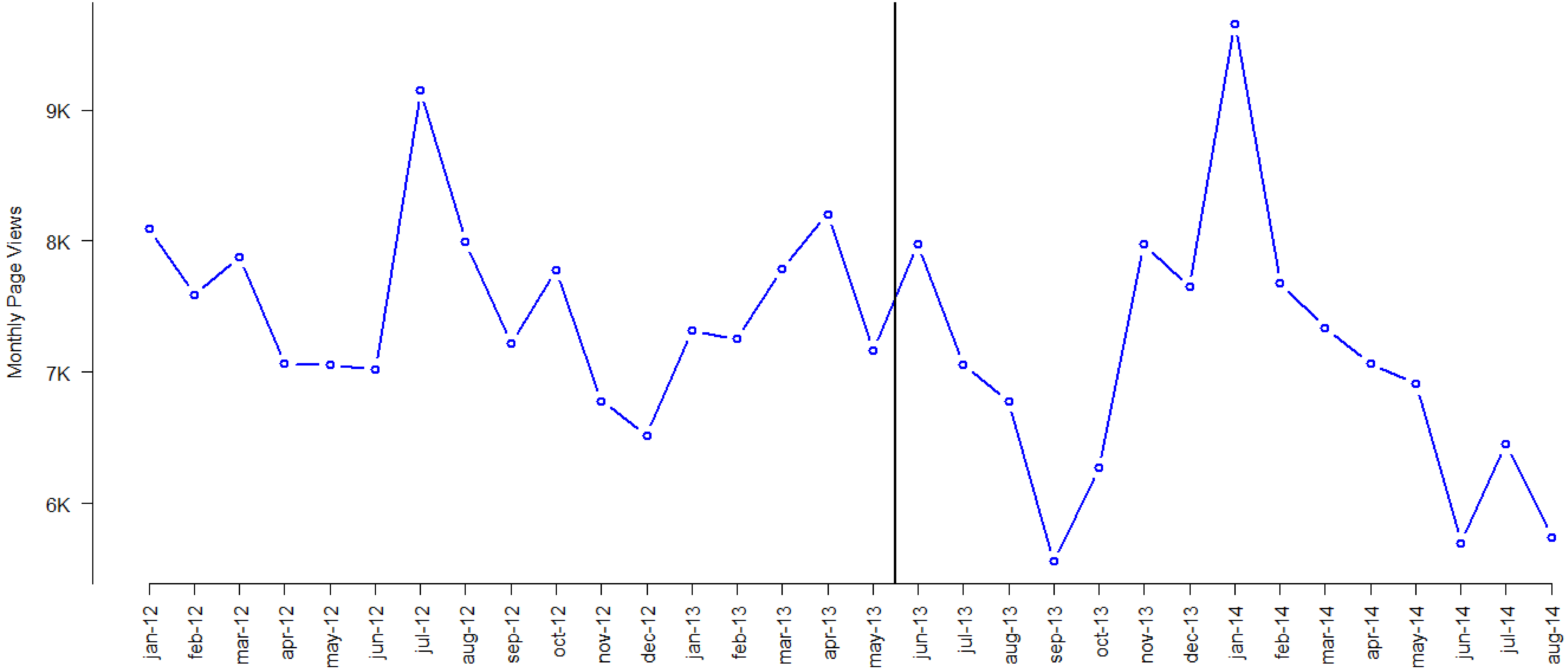

Infrastructure: Page Views for information_infrastructure
Monthly Page Views
8K
7K
6K
5K
4K
3K
2K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14


Infrastructure: Page Views for infrastructure_security
Monthly Page Views
1.3K
1.2K
1.1K
1K
0.9K
0.8K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

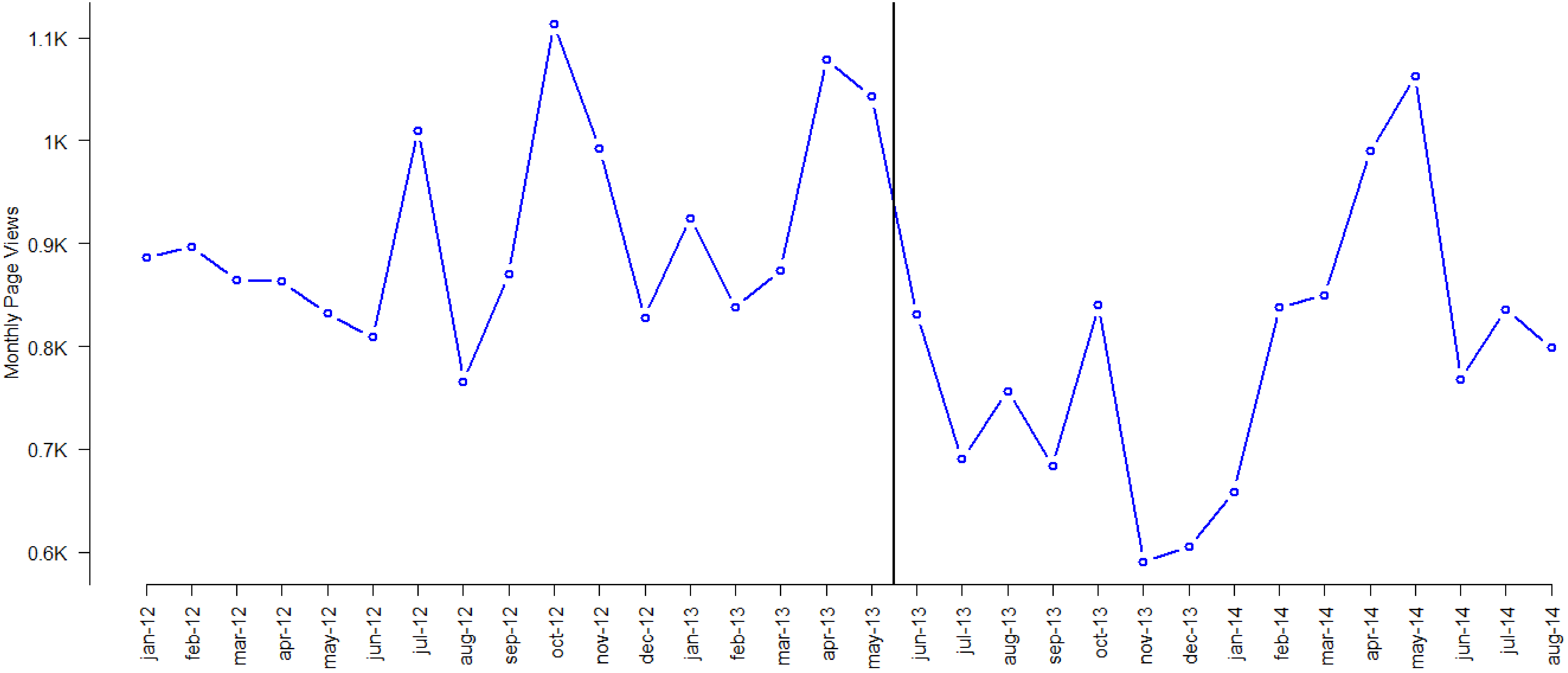
# Infrastructure: Page Views for metro_station

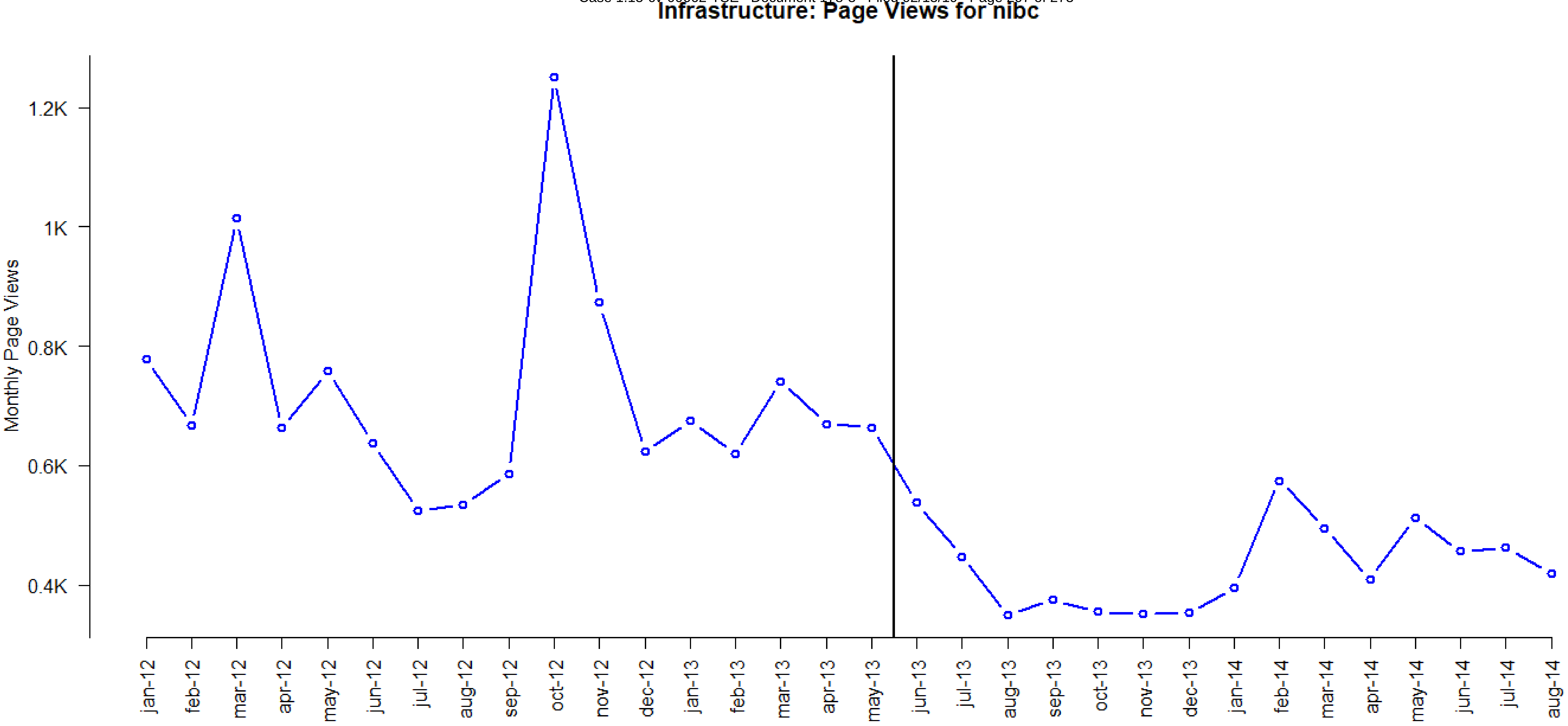


## Infrastructure: Page Views for Metropolitan_Atlanta_Rapid_Trans

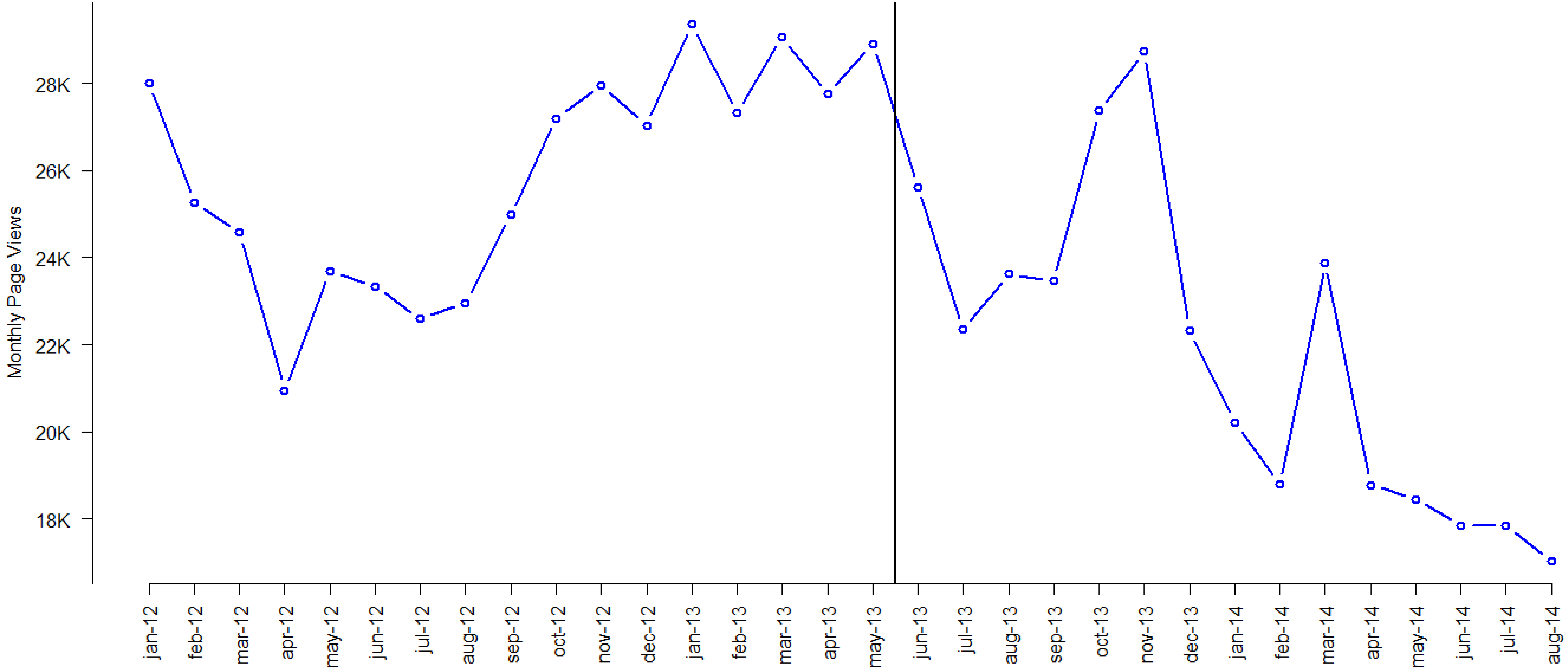


# Infrastructure: Page Views for national_information_infrastruct

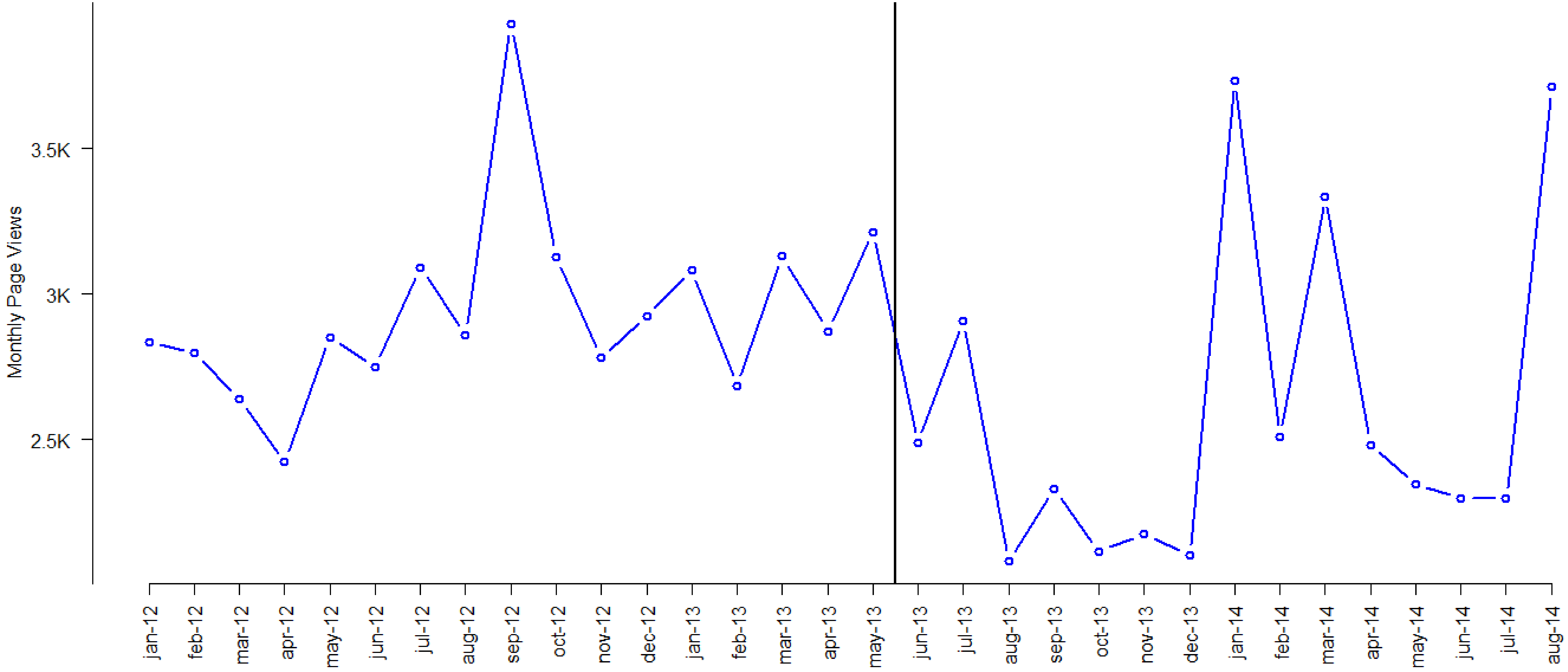


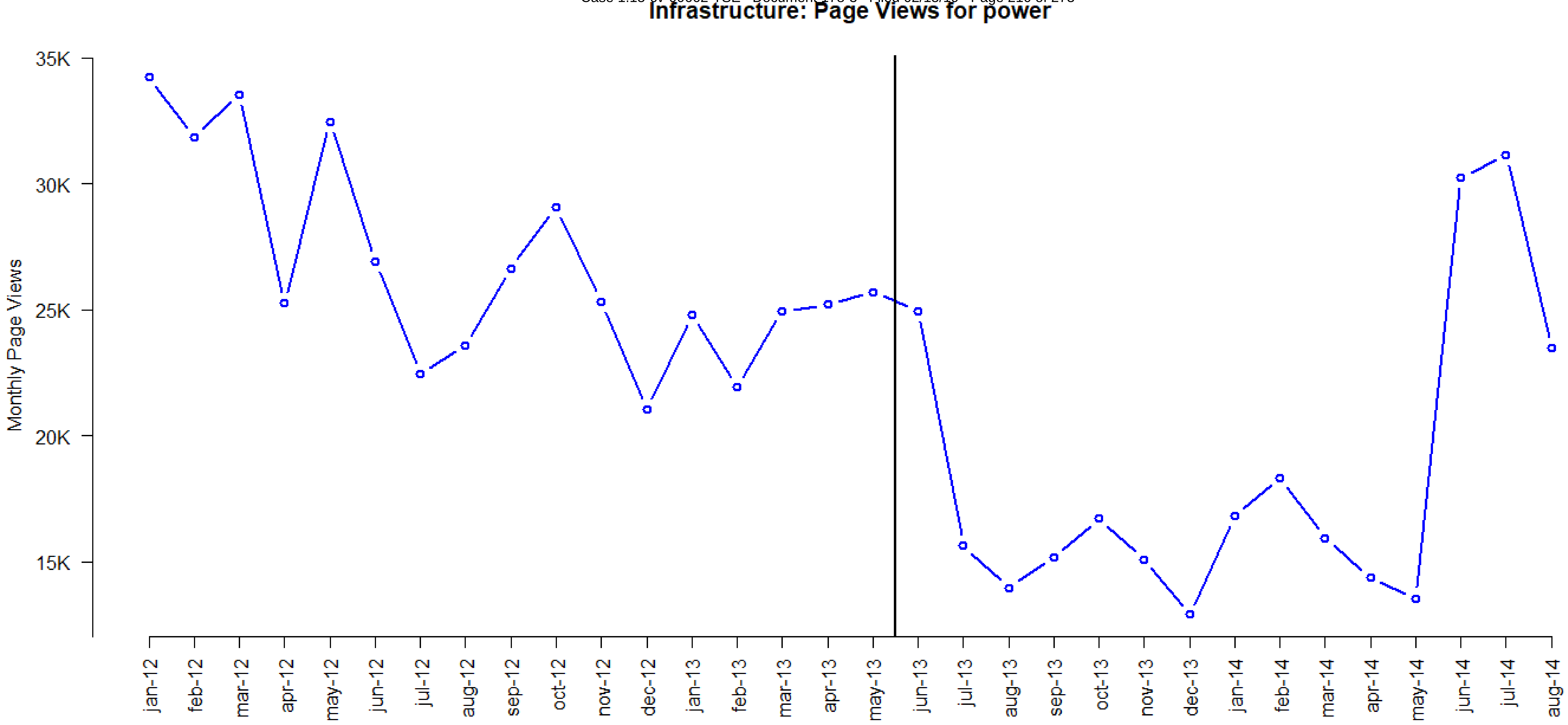

Infrastructure: Page Views for nibc
Monthly Page Views
1.2K
1K
0.8K
0.6K
0.4K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

## Infrastructure: Page Views for port

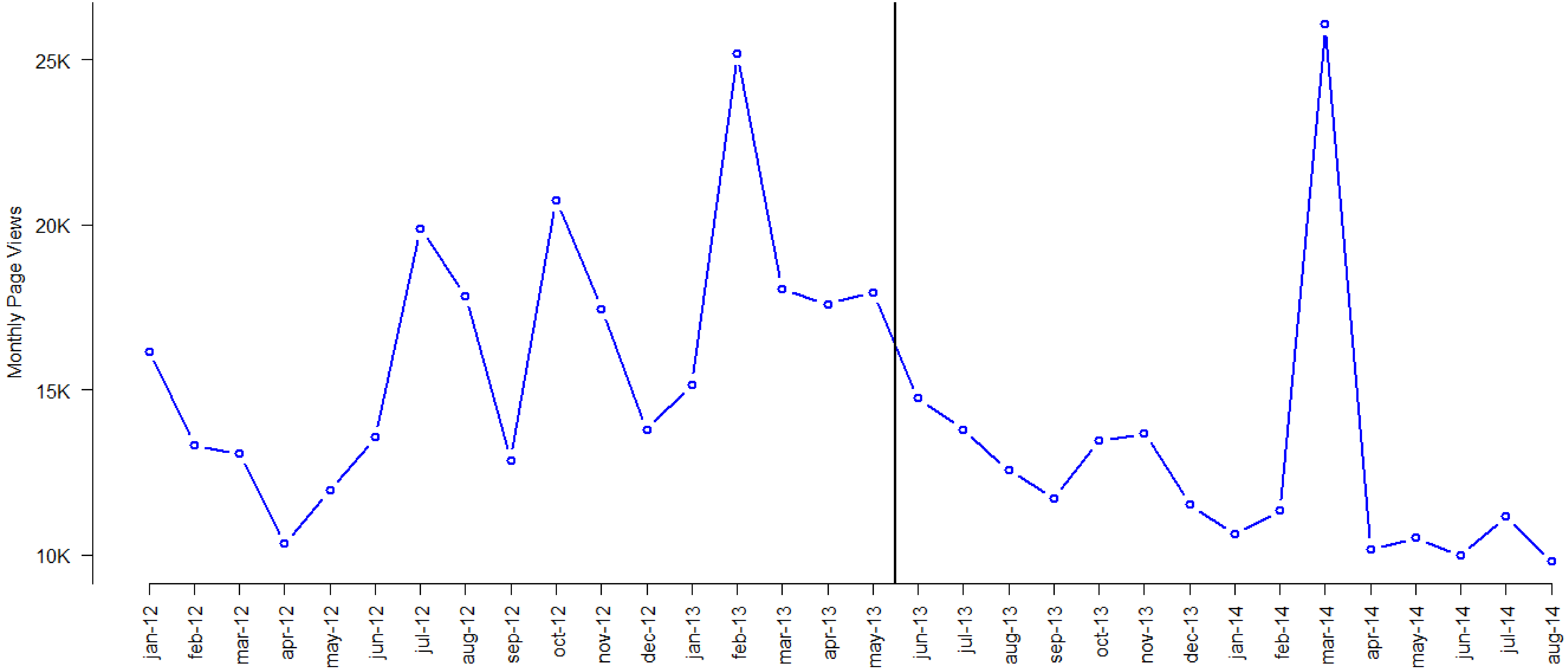


# Infrastructure: Page Views for Port_authority

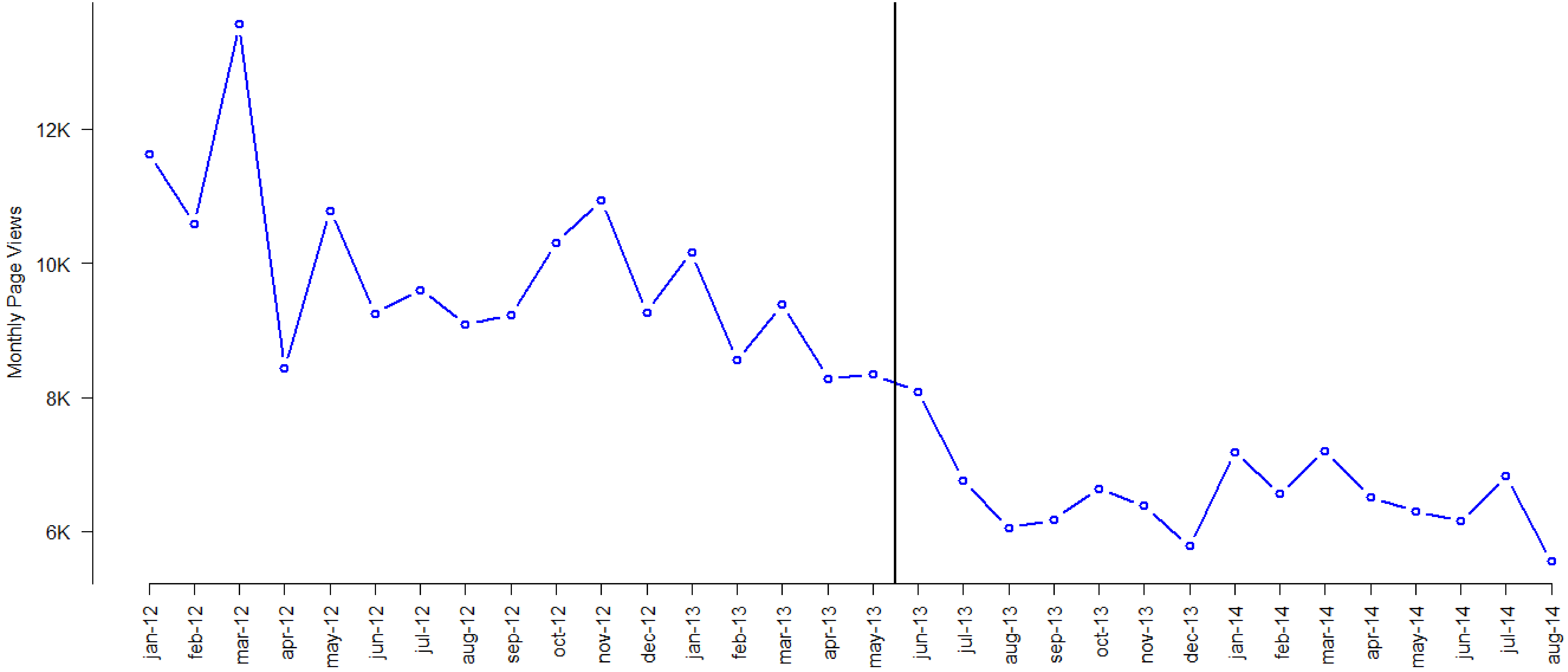


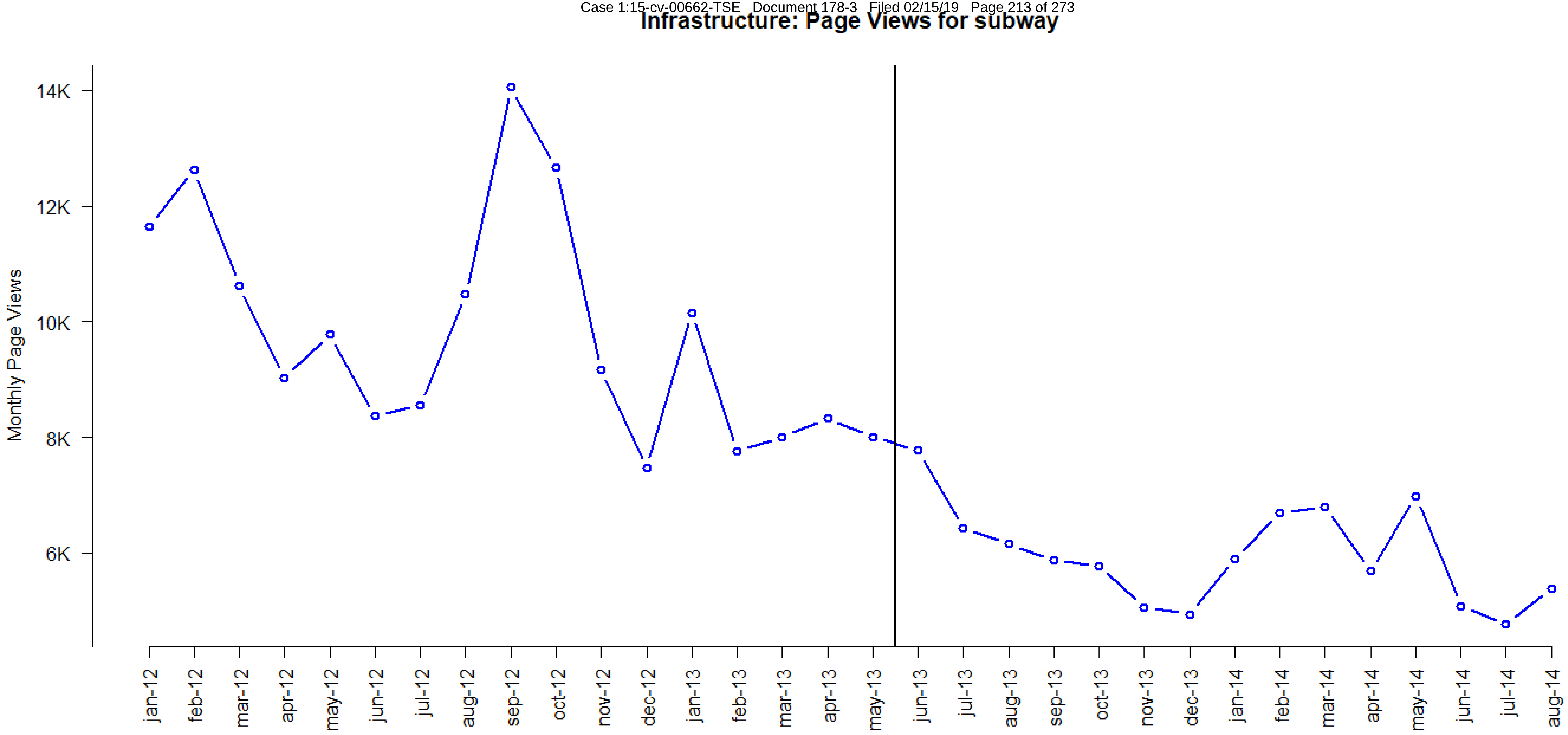

Infrastructure: Page Views for power
Monthly Page Views
35K
30K
25K
20K
15K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

# Infrastructure: Page Views for power_outage

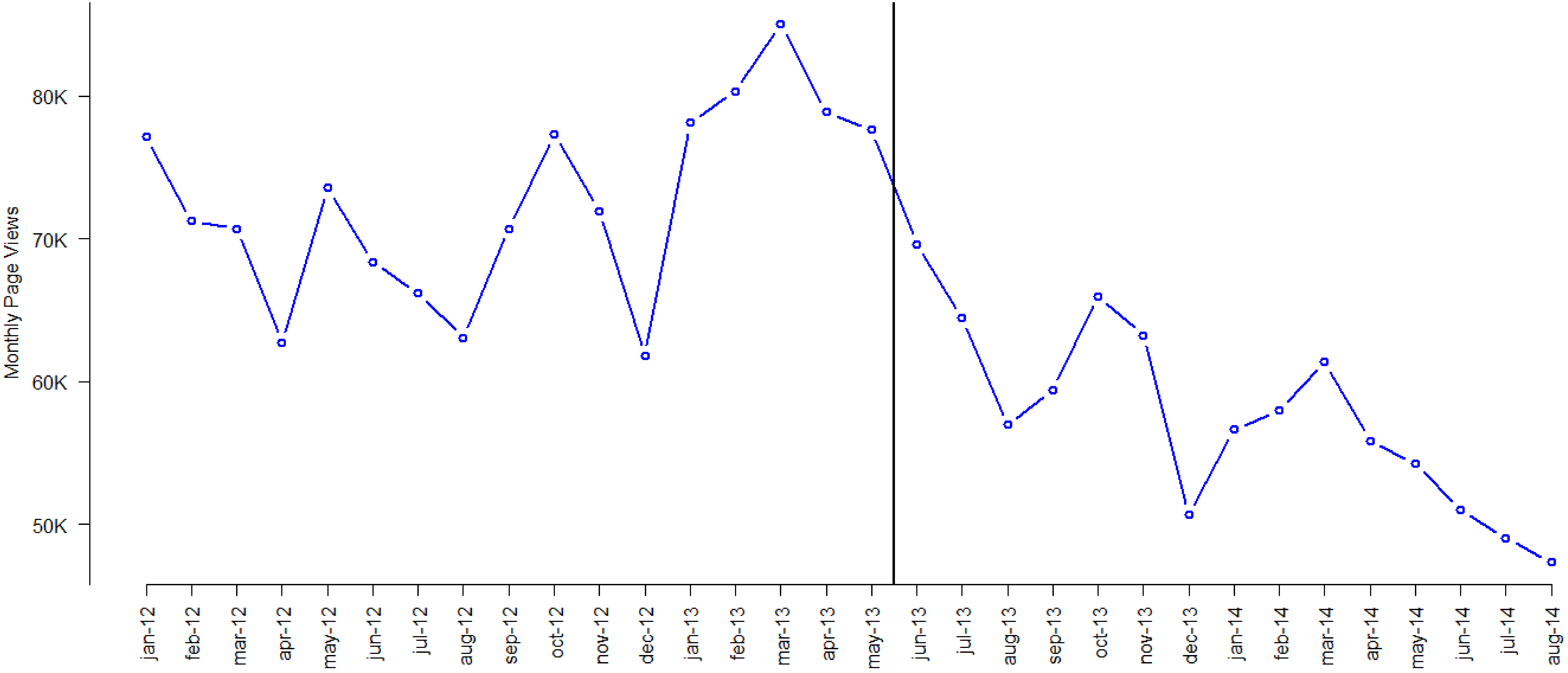


# Infrastructure: Page Views for smart

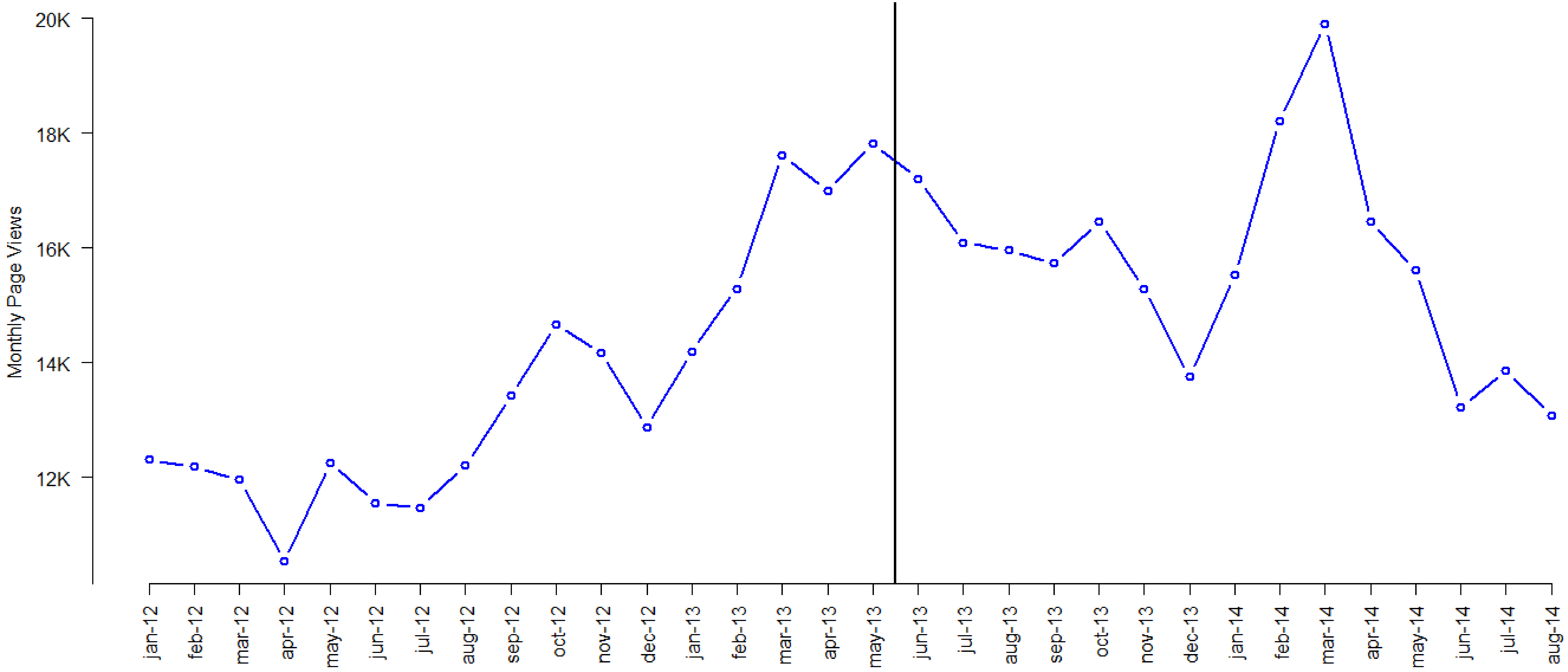



Infrastructure: Page Views for subway
Monthly Page Views
14K
12K
10K
8K
6K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

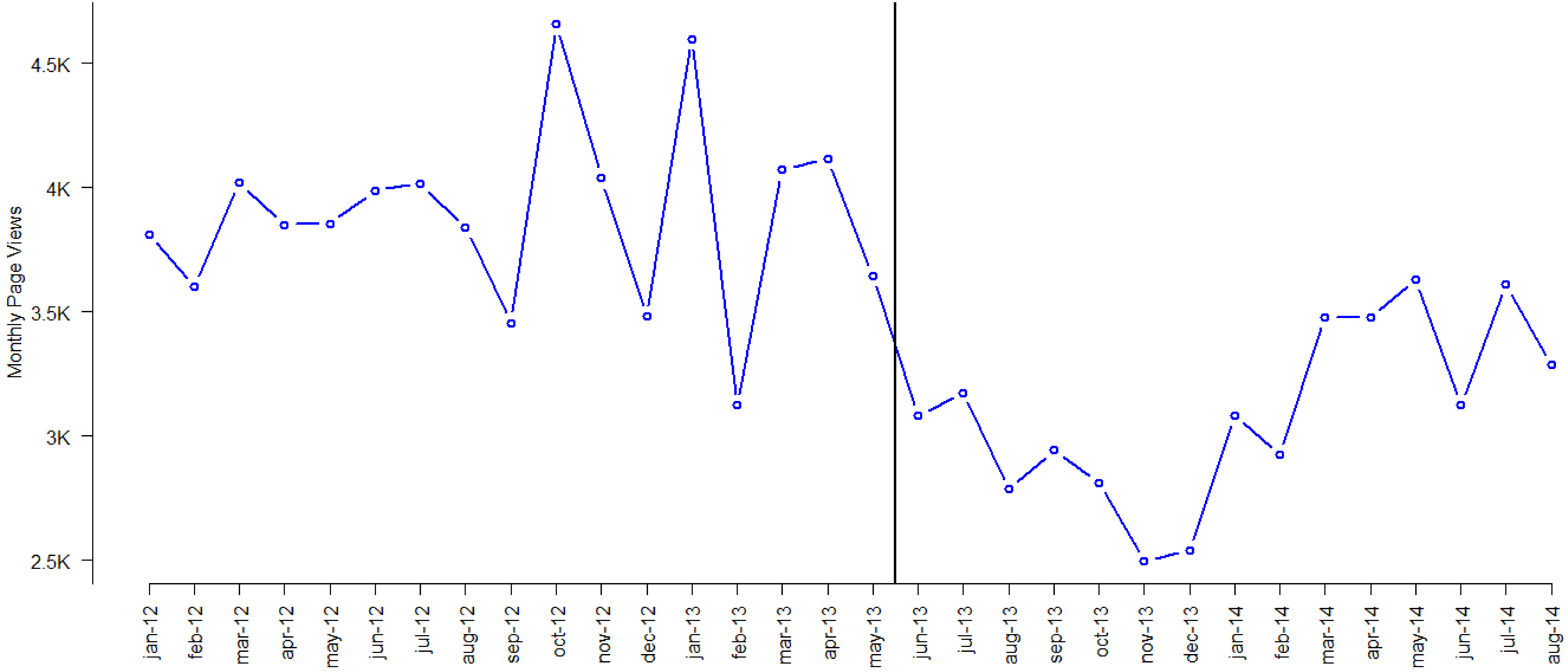
## Infrastructure: Page Views for telecommunication

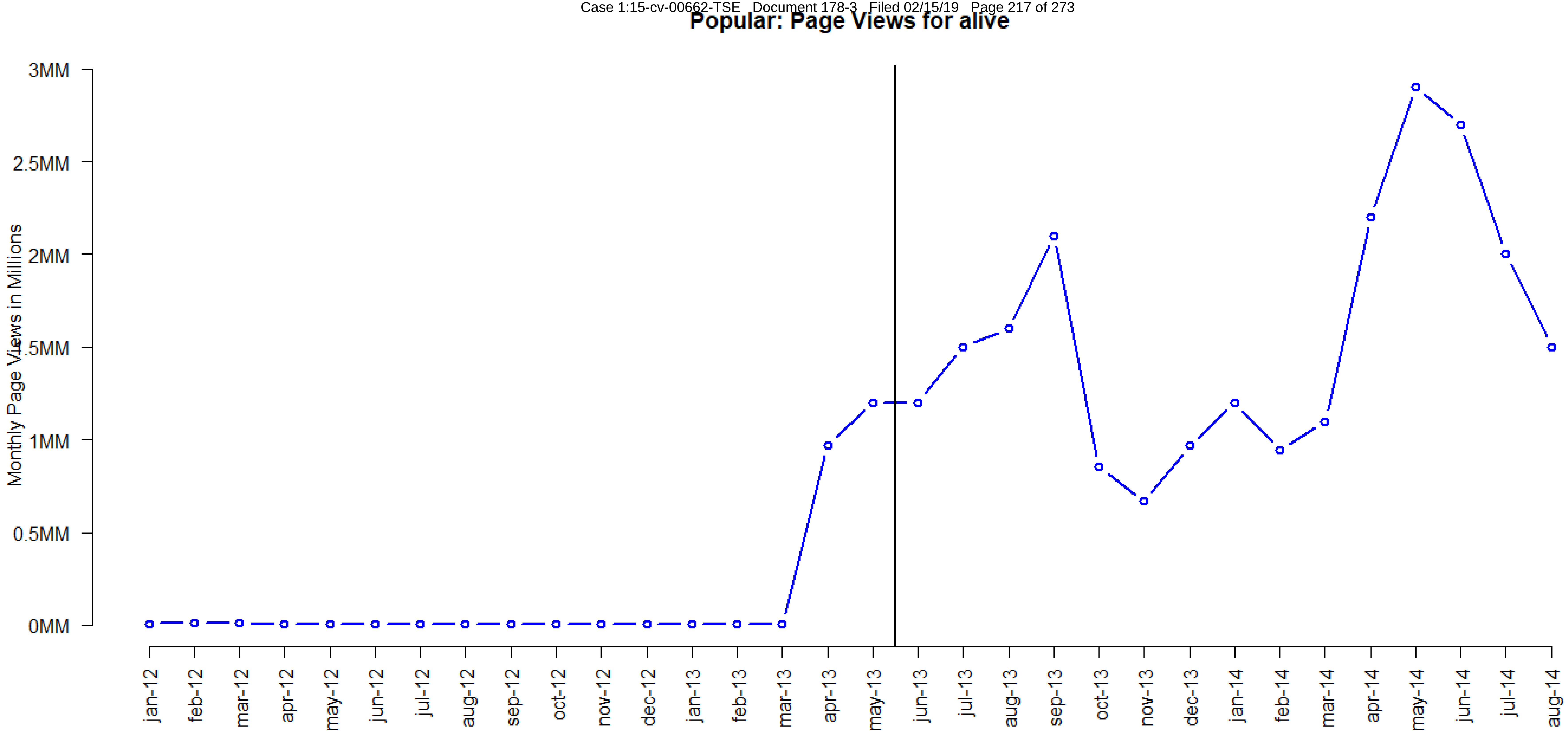


## Infrastructure: Page Views for Telecommunications_network

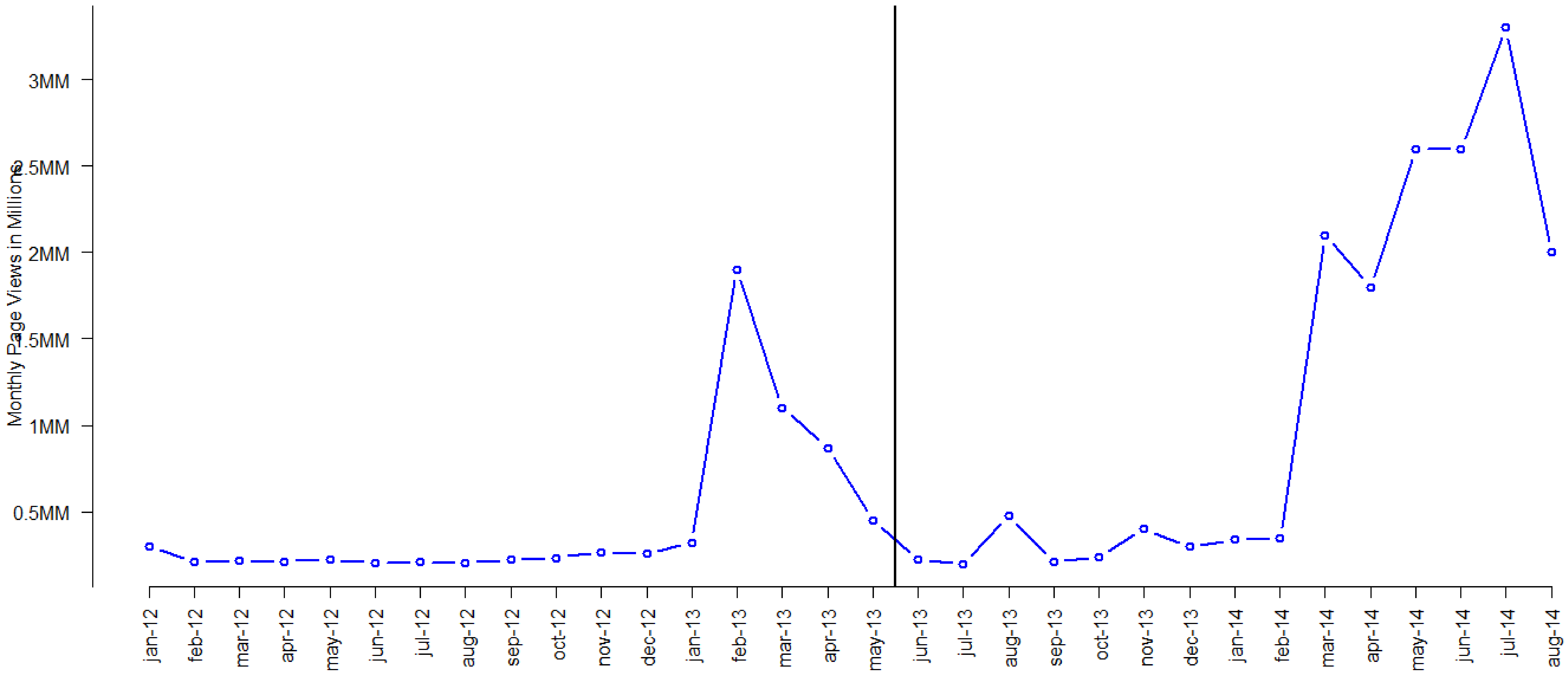


# Infrastructure: Page Views for washington_metropolitan_area_tra

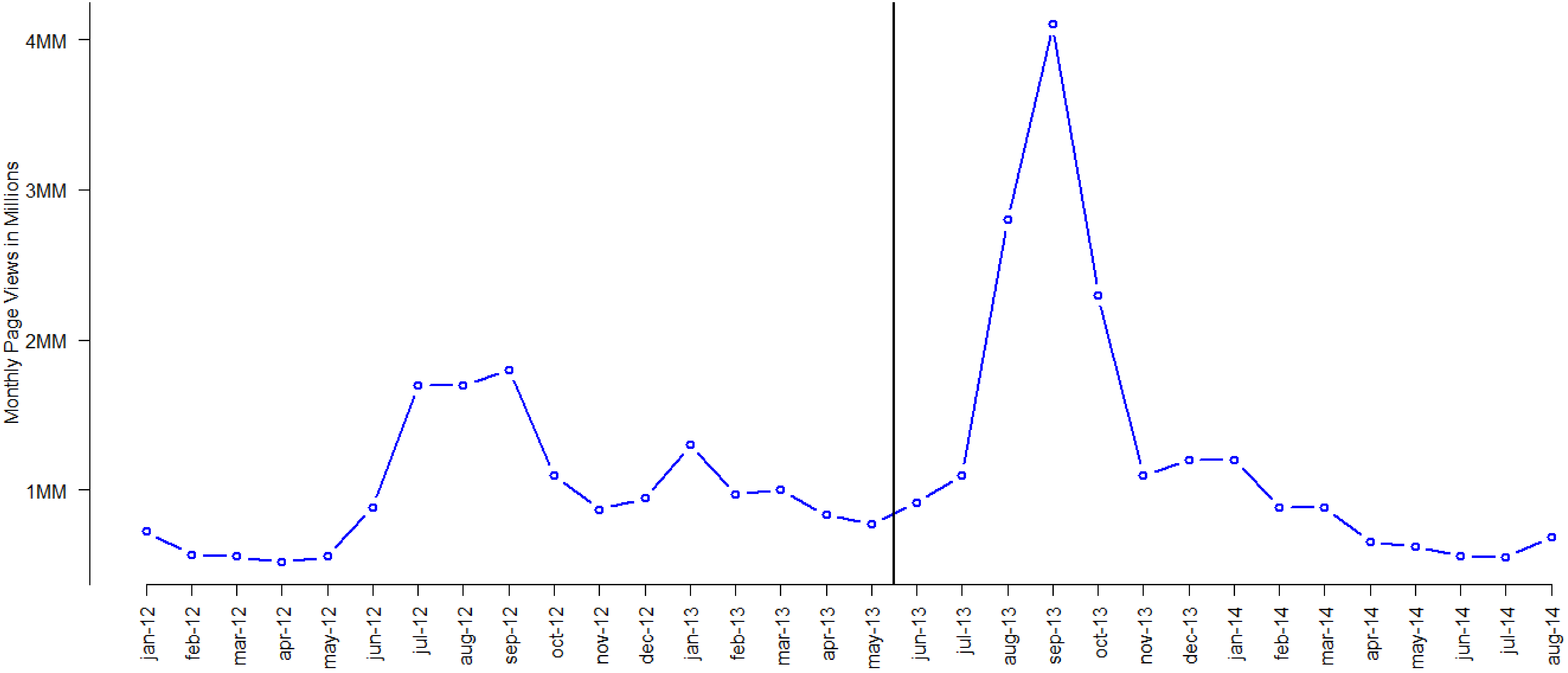



Popular: Page Views for alive
Monthly Page Views in Millions
3MM
2.5MM
2MM
1.5MM
1MM
0.5MM
0MM
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

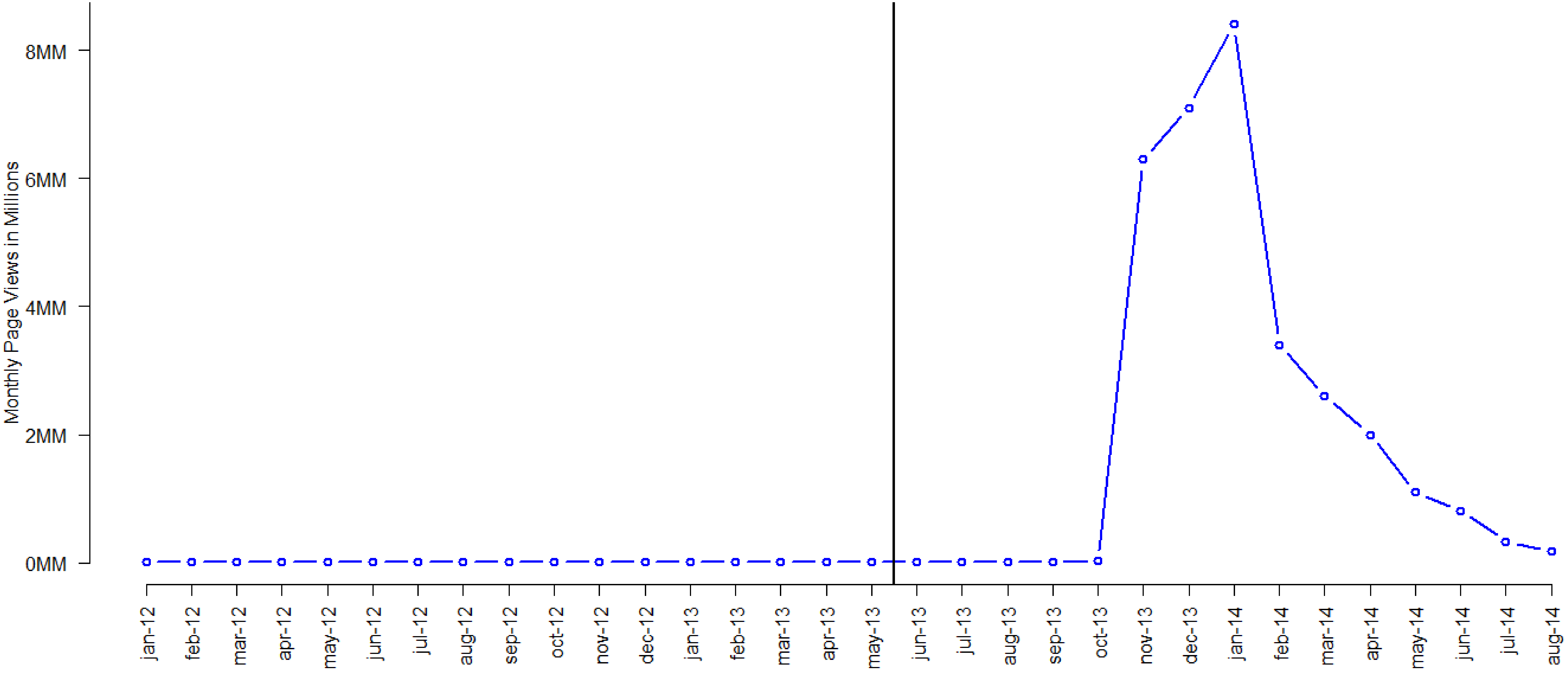
# Popular: Page Views for amazoncom



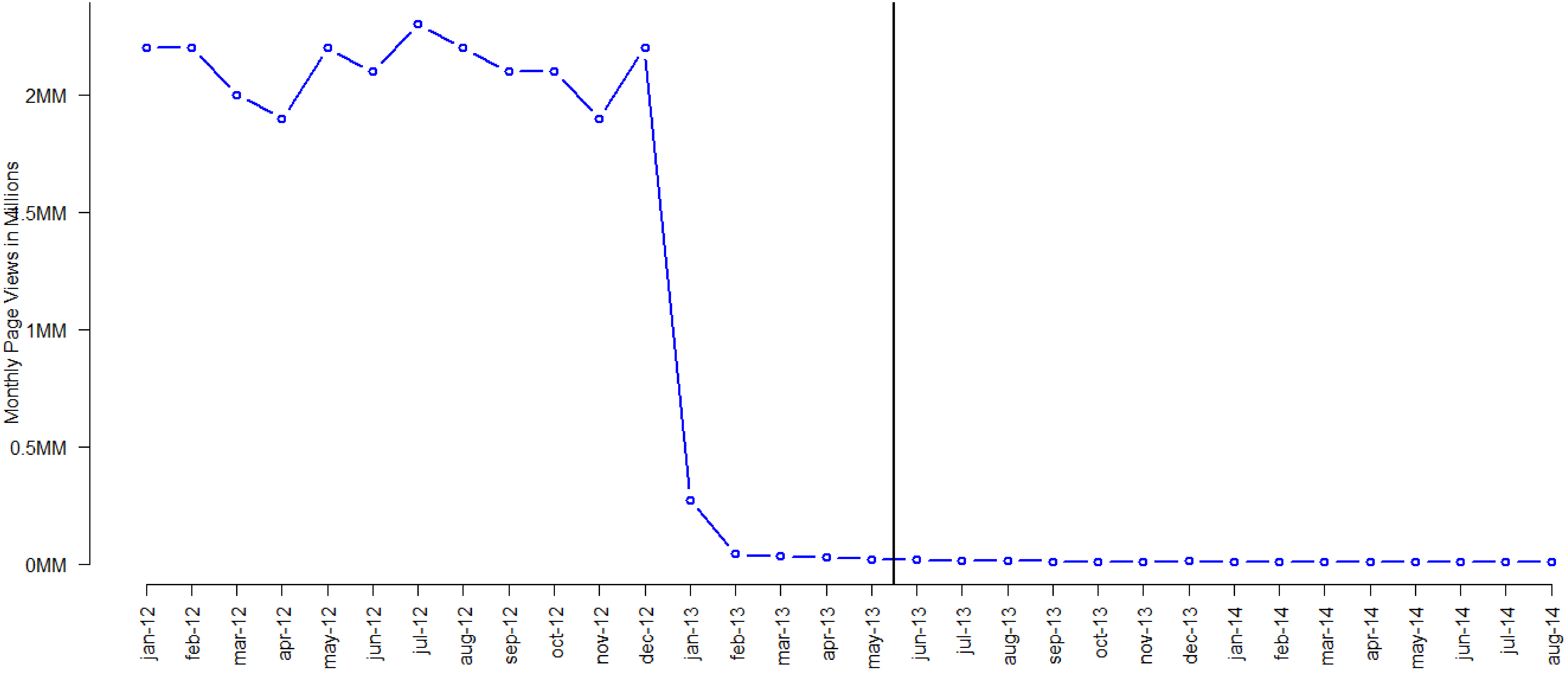
## Popular: Page Views for breaking_bad



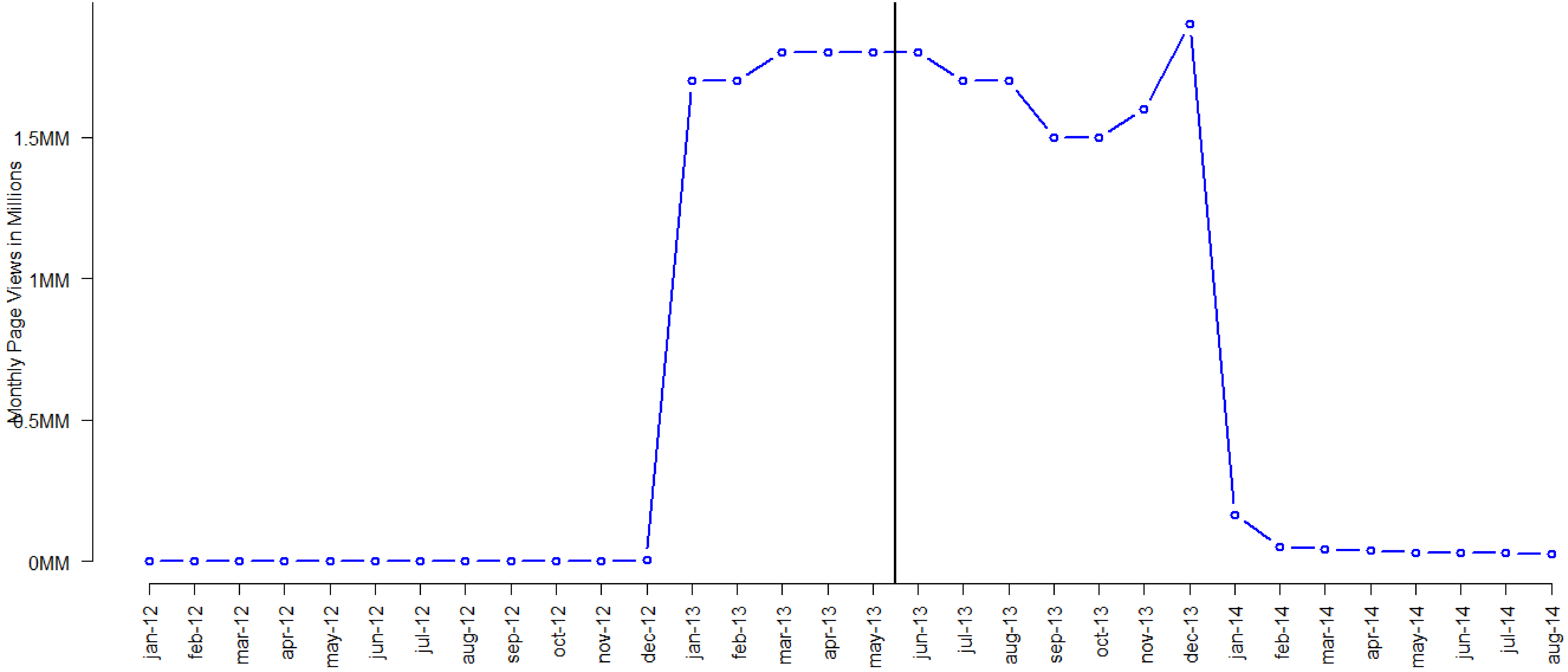
## Popular: Page Views for climatic_research_unit_email_con



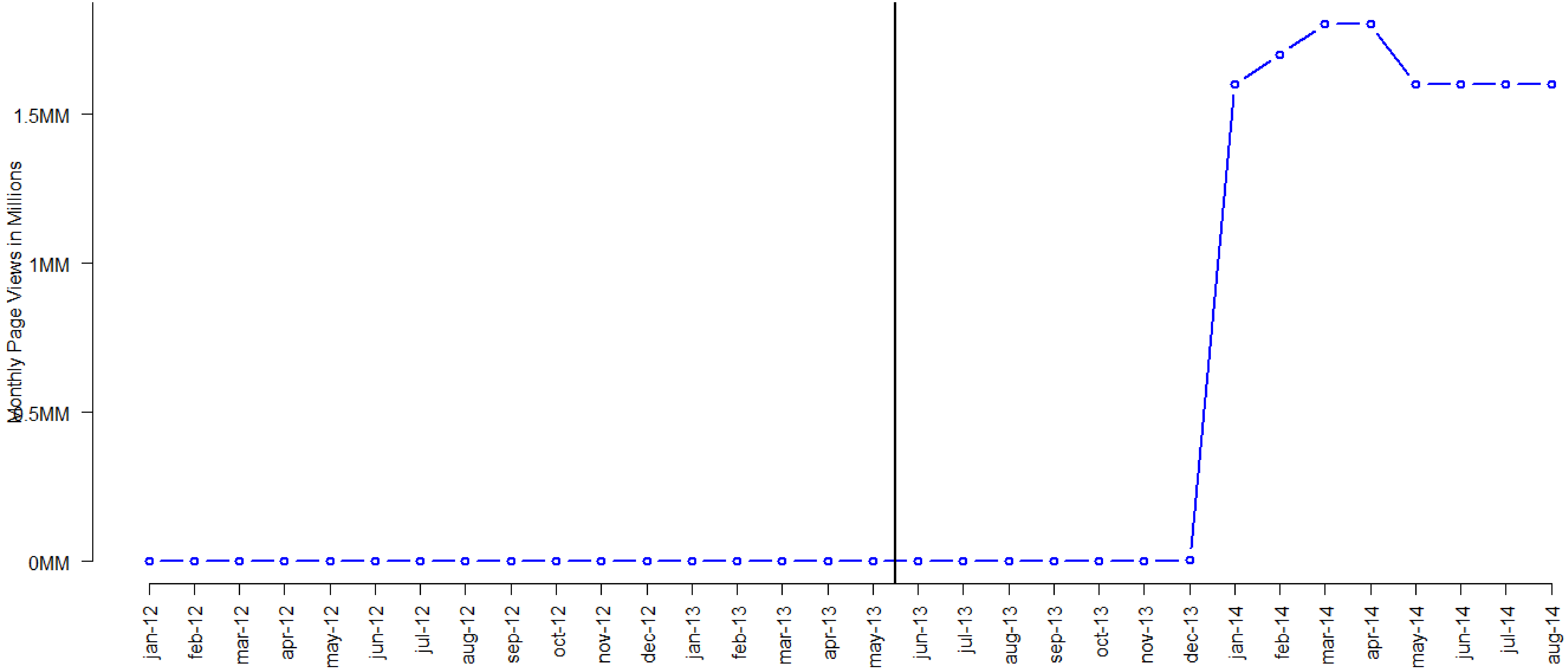
## Popular: Page Views for deaths_in_2012



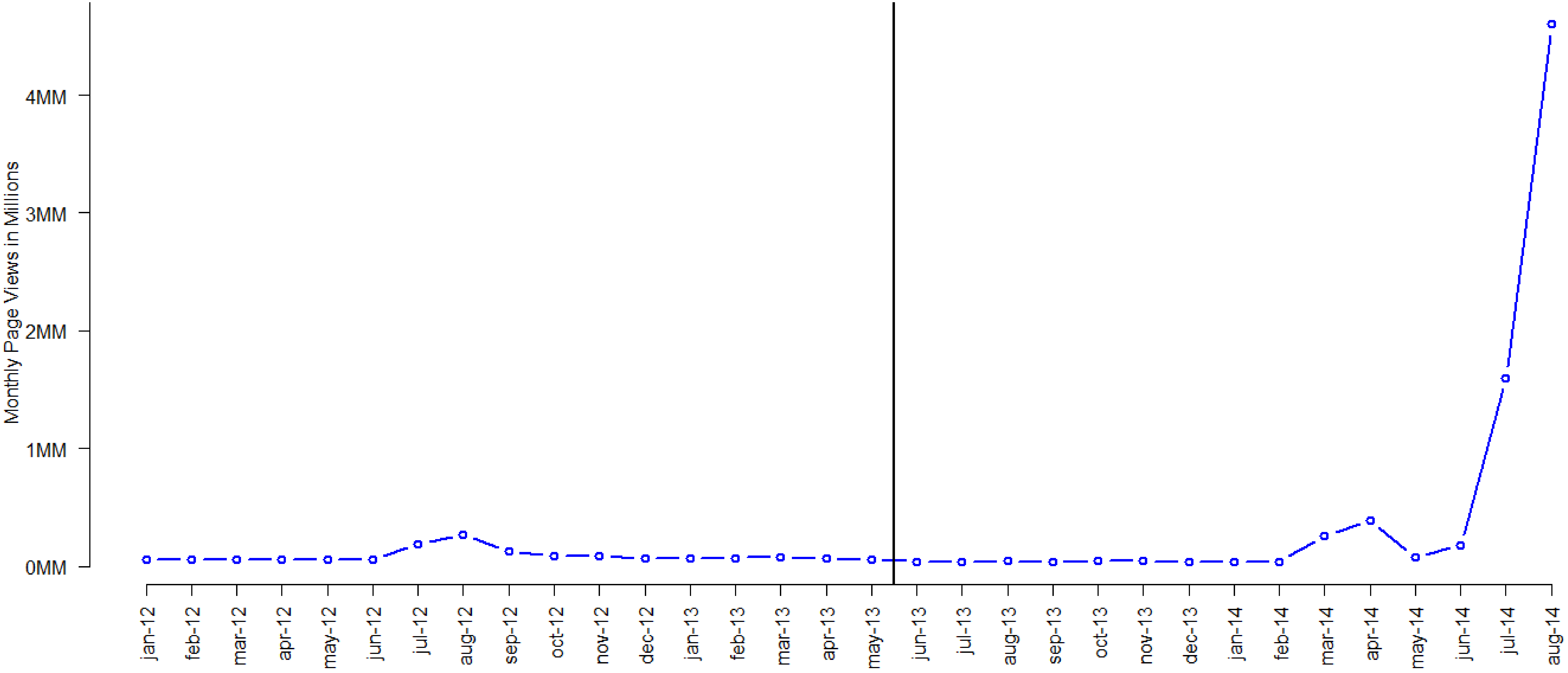
# Popular: Page Views for deaths_in_2013



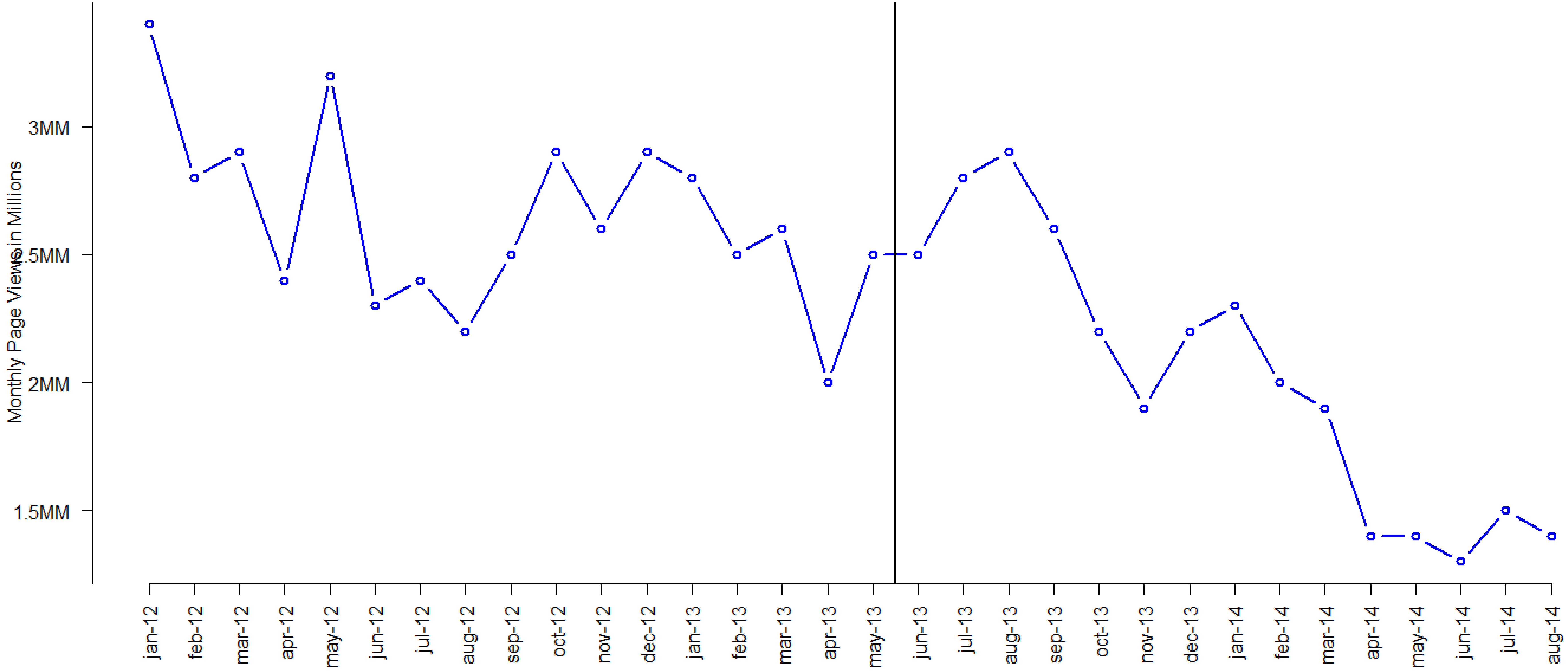
# Popular: Page Views for deaths_in_2014

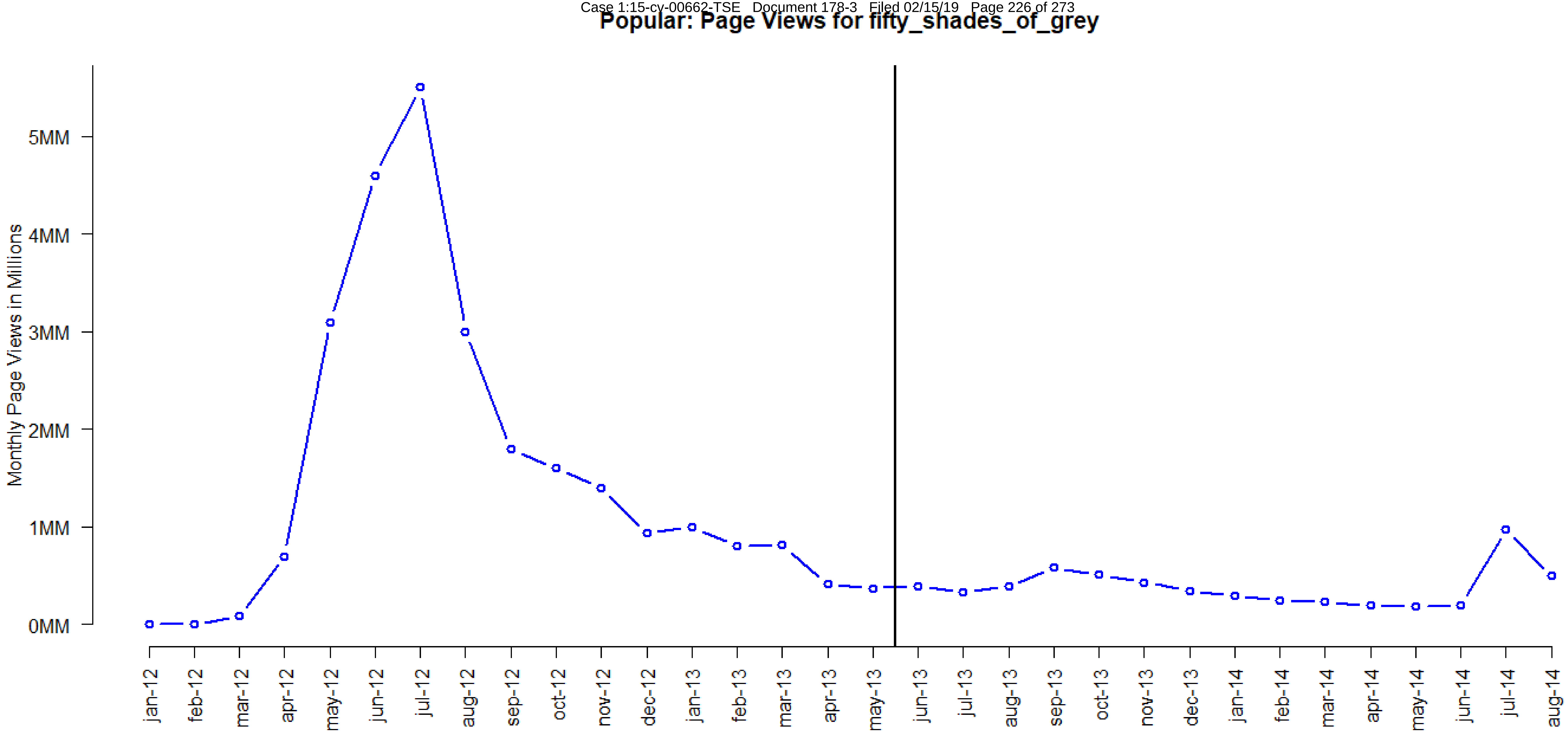


# Popular: Page Views for ebola_virus_disease_

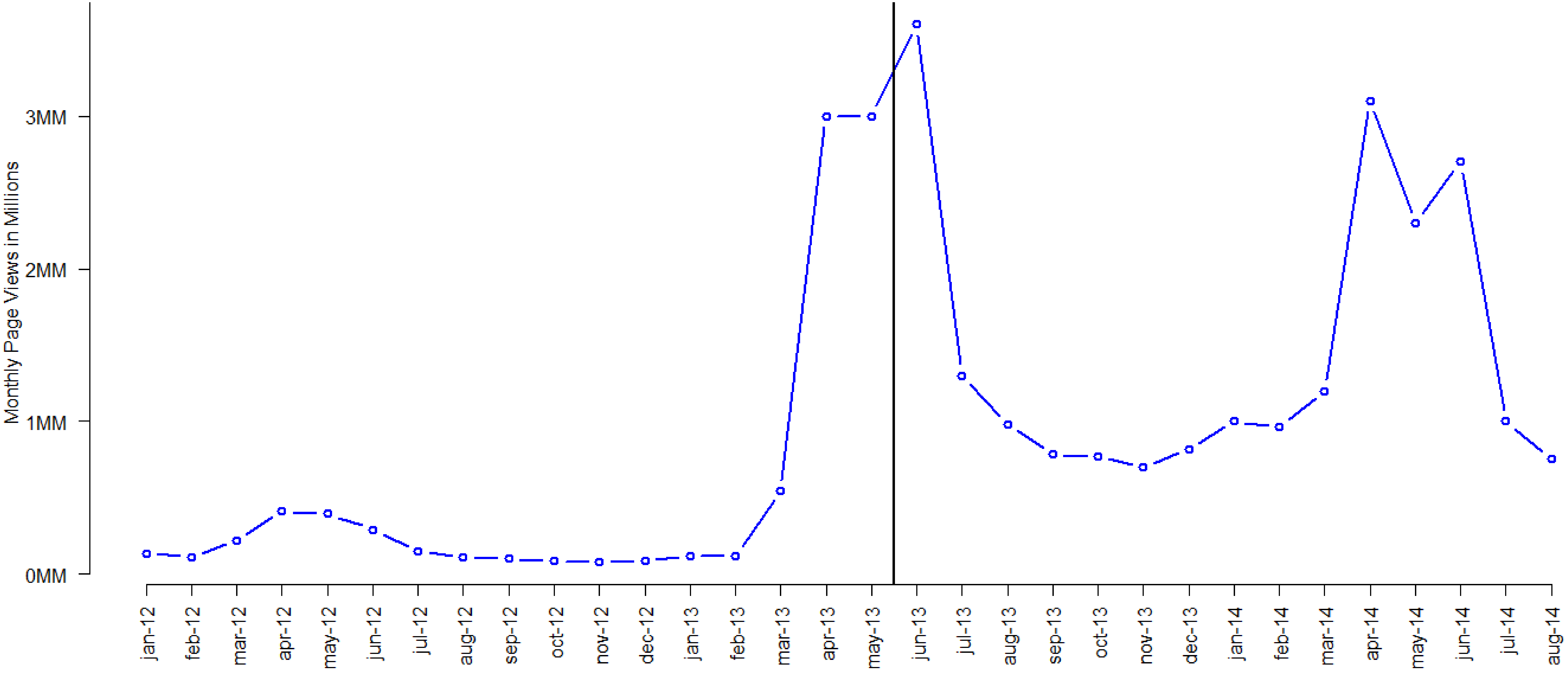


# Popular: Page Views for facebook

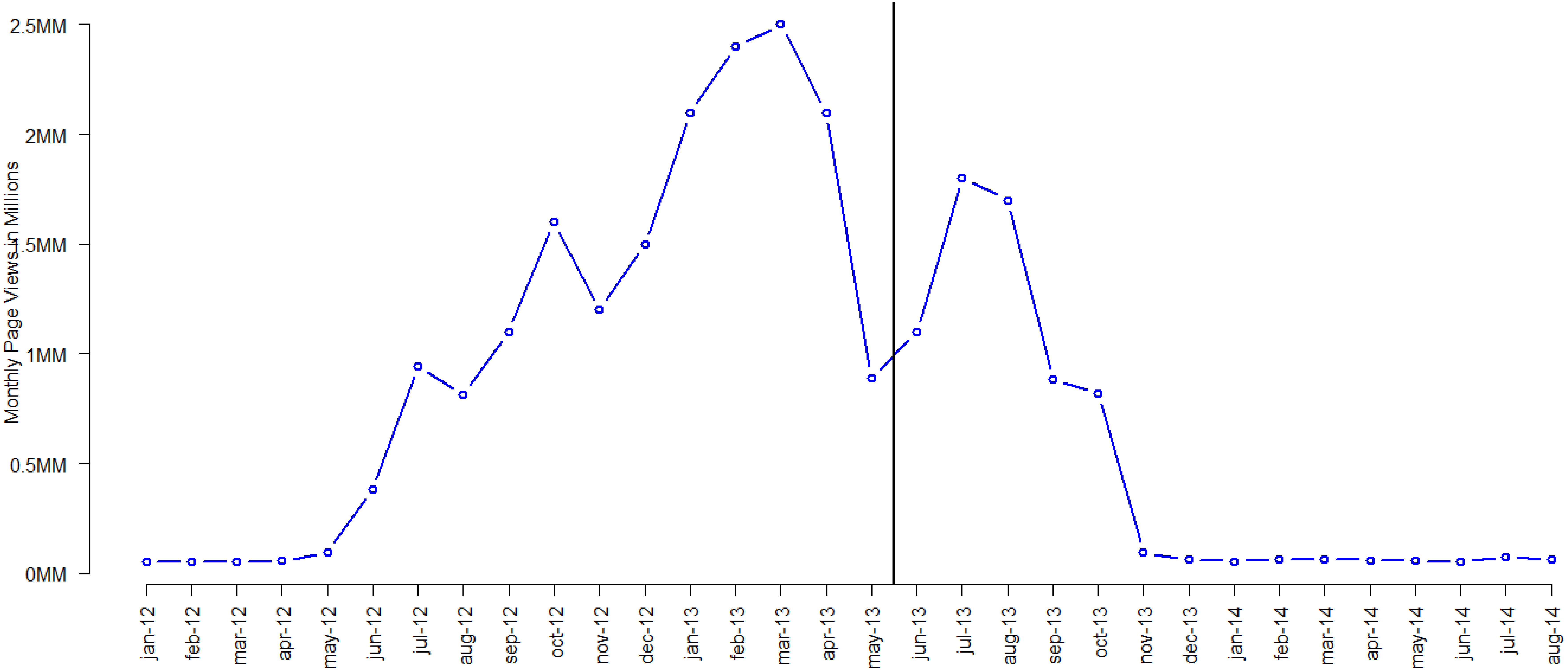


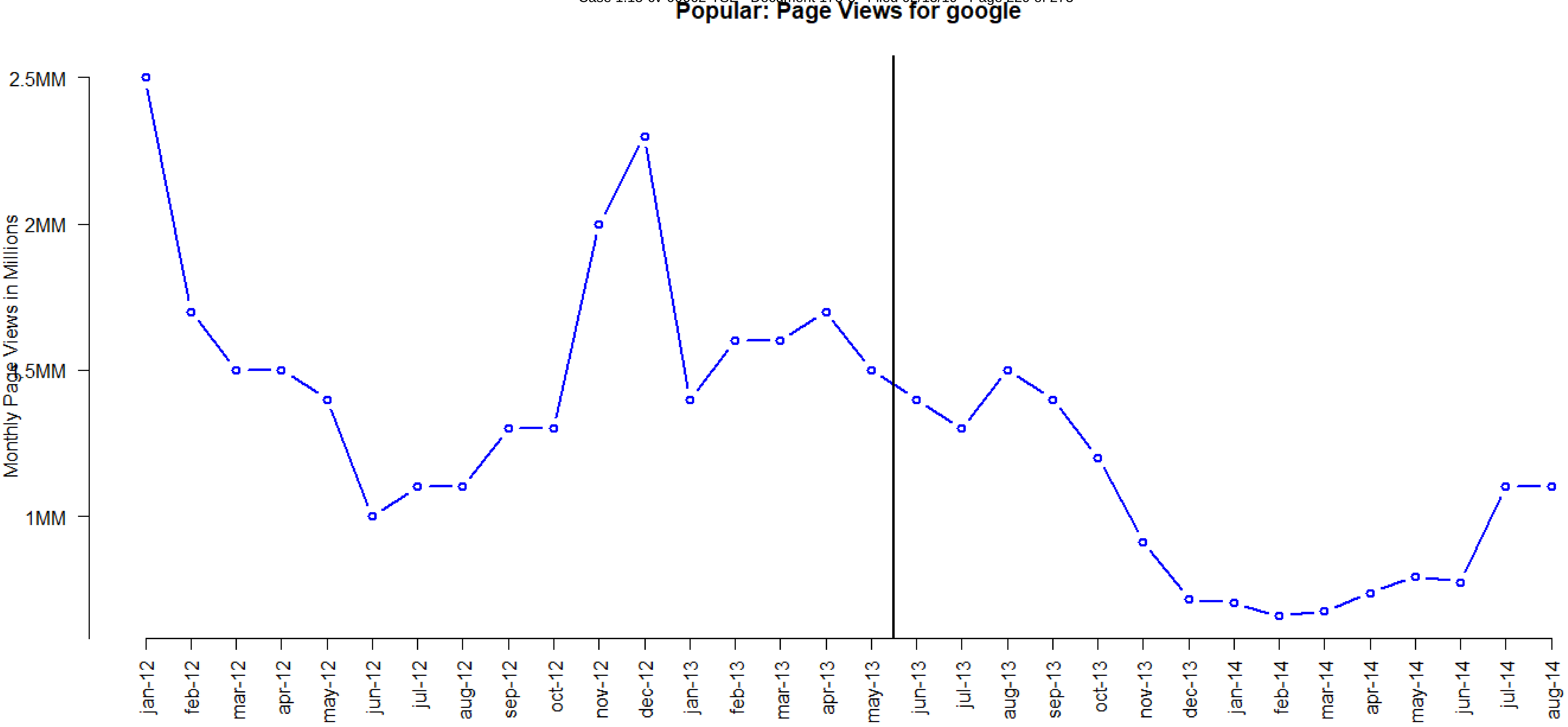

Popular: Page Views for fifty_shades_of_grey
Monthly Page Views in Millions
5MM
4MM
3MM
2MM
1MM
0MM
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

# Popular: Page Views for game_of_thrones

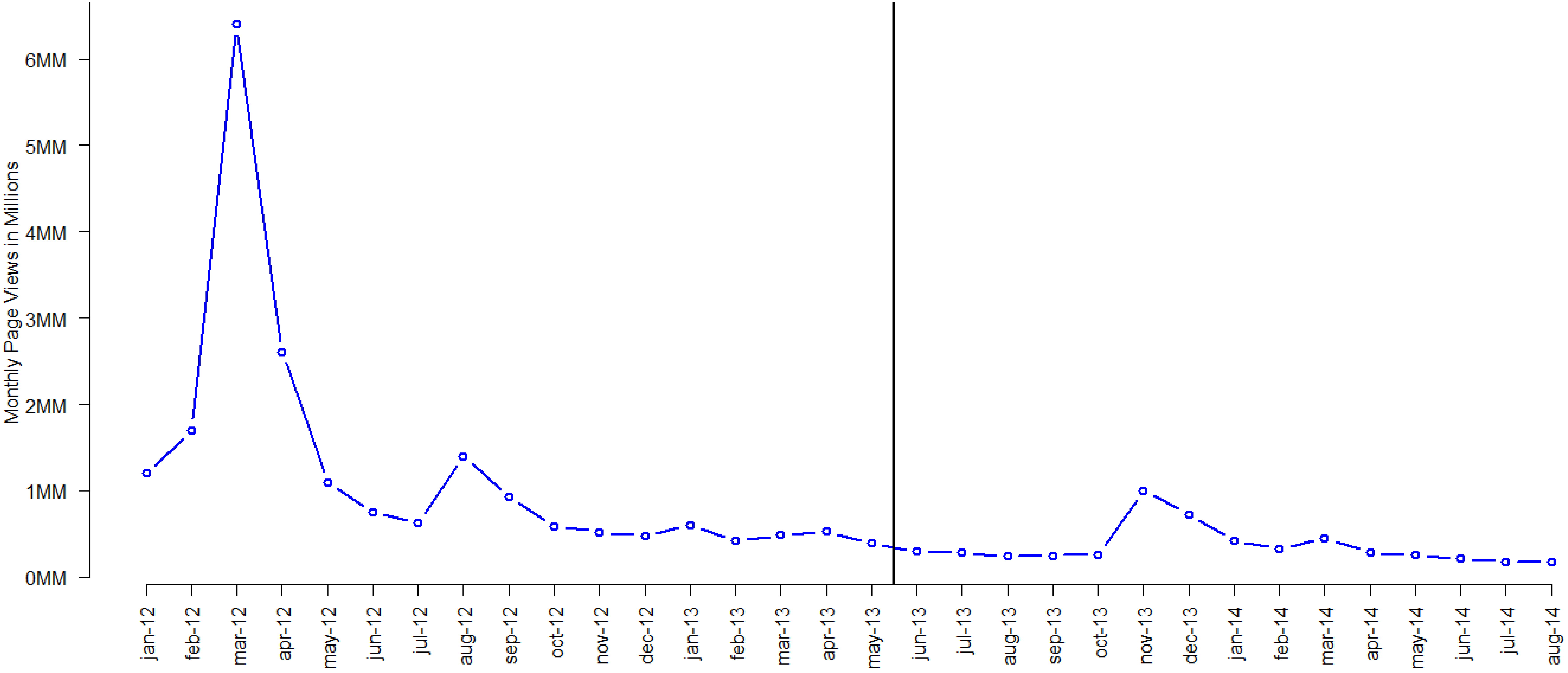


## Popular: Page Views for gforce

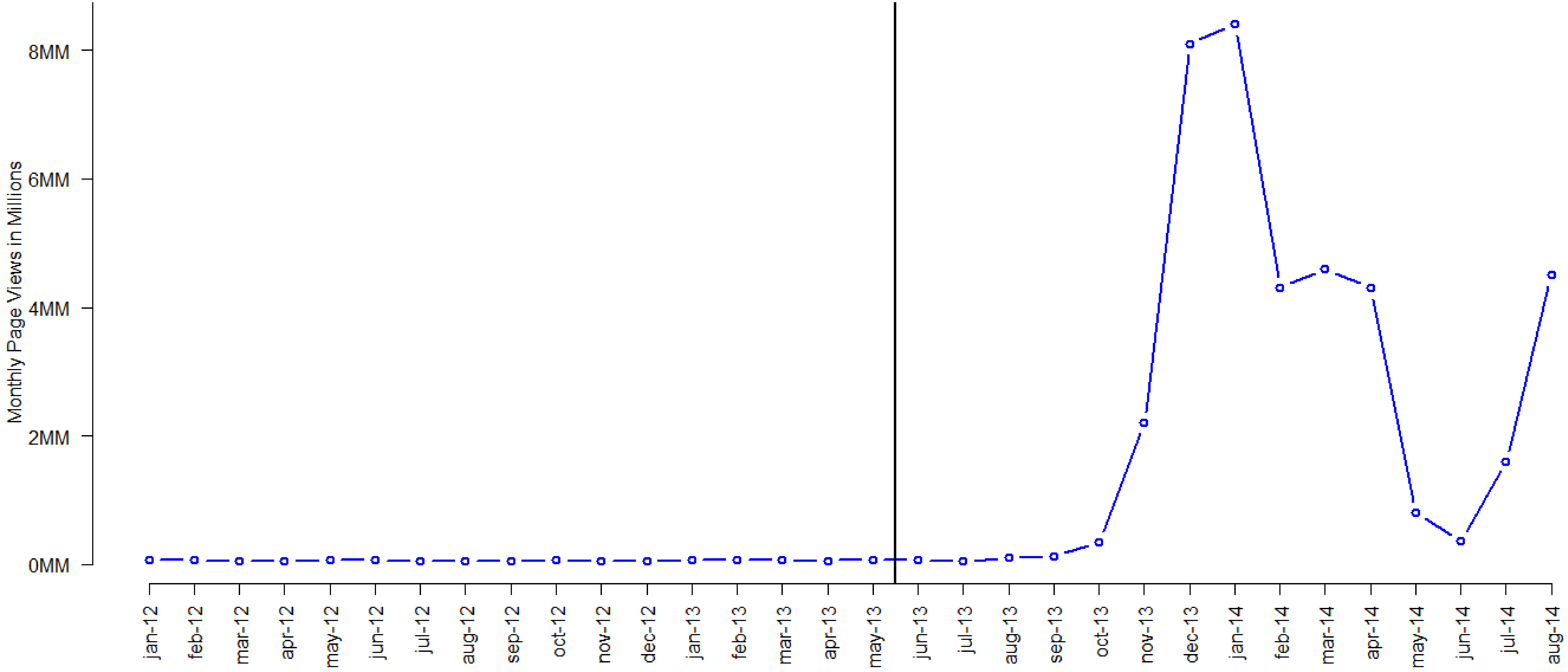



Popular: Page Views for google
Monthly Page Views in Millions
2.5MM
2MM
1.5MM
1MM
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

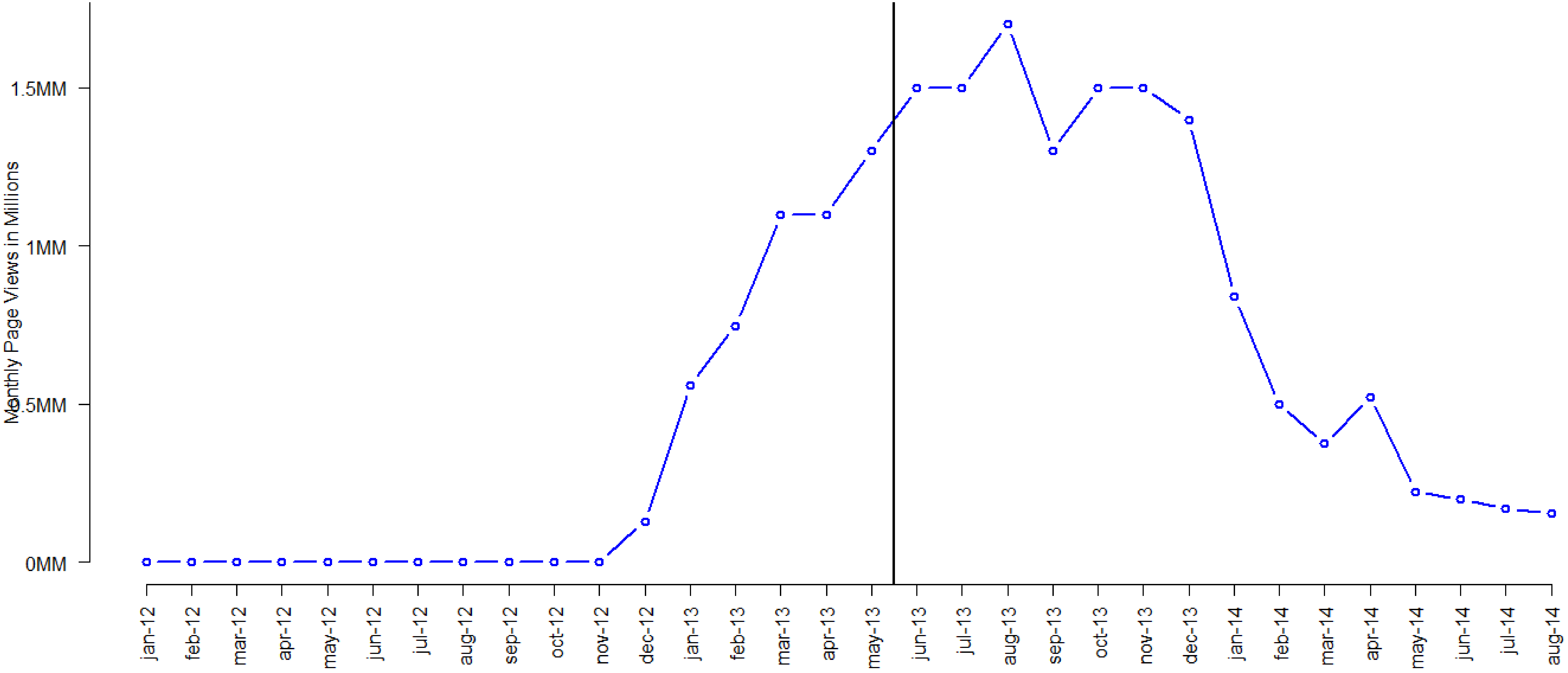
# Popular: Page Views for hunger_games

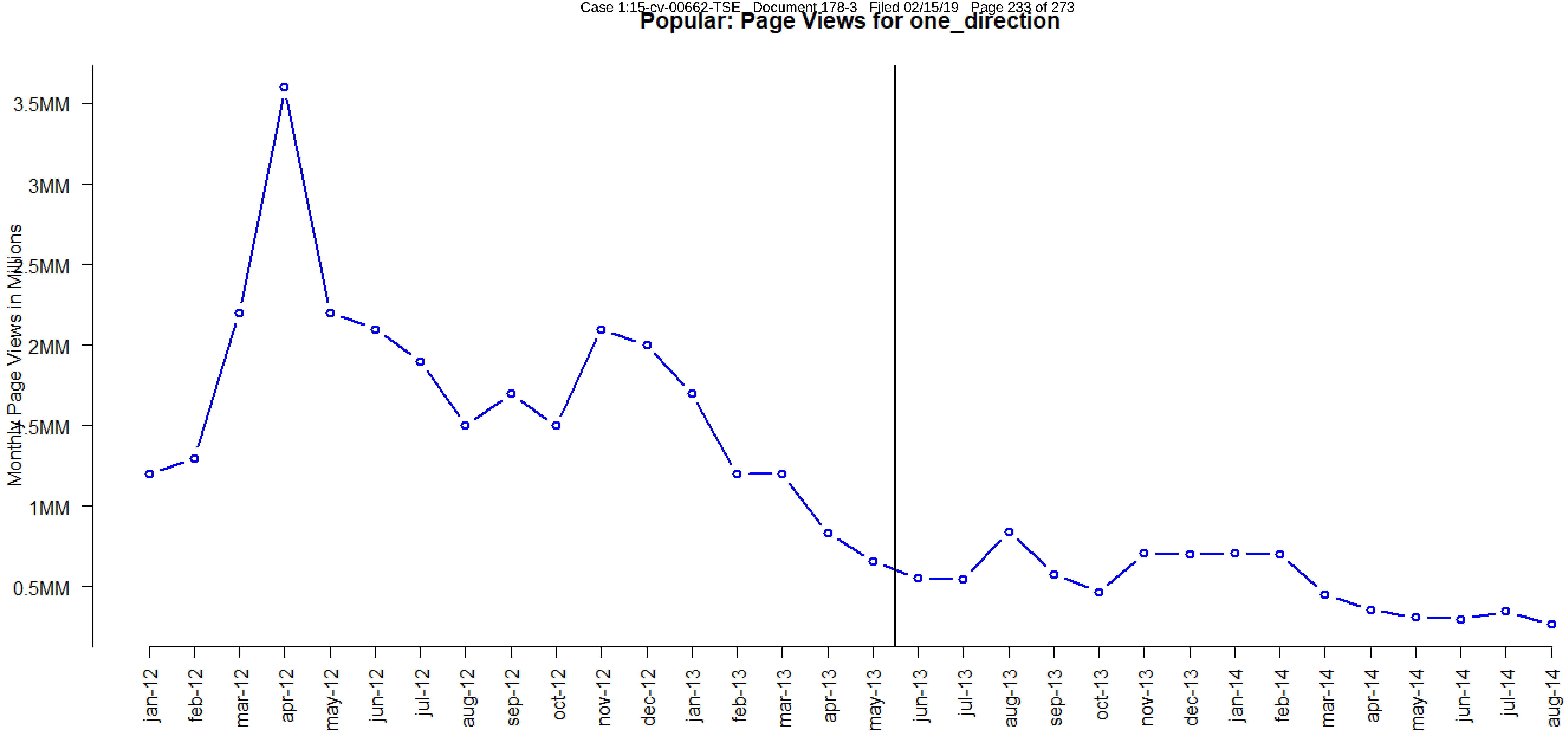


# Popular: Page Views for java

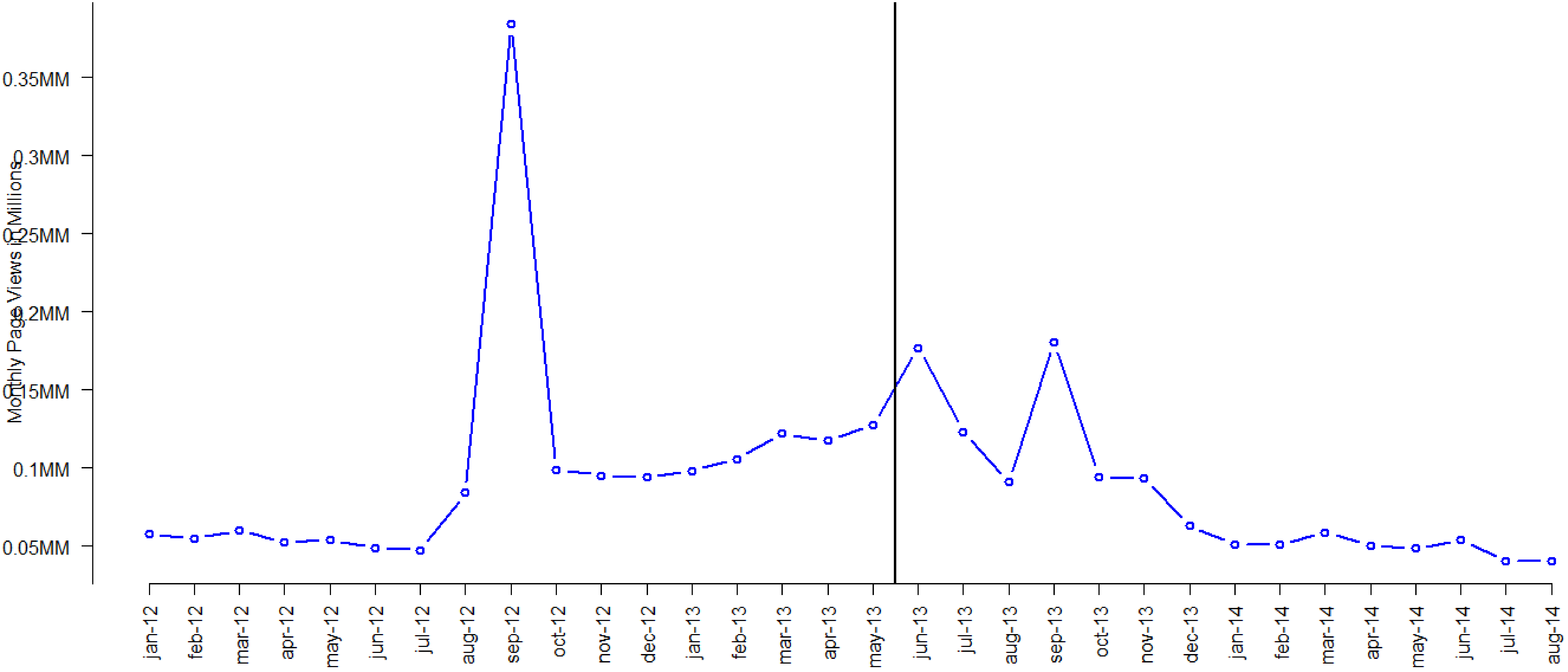


## Popular: Page Views for list_of_bollywood_films_2013

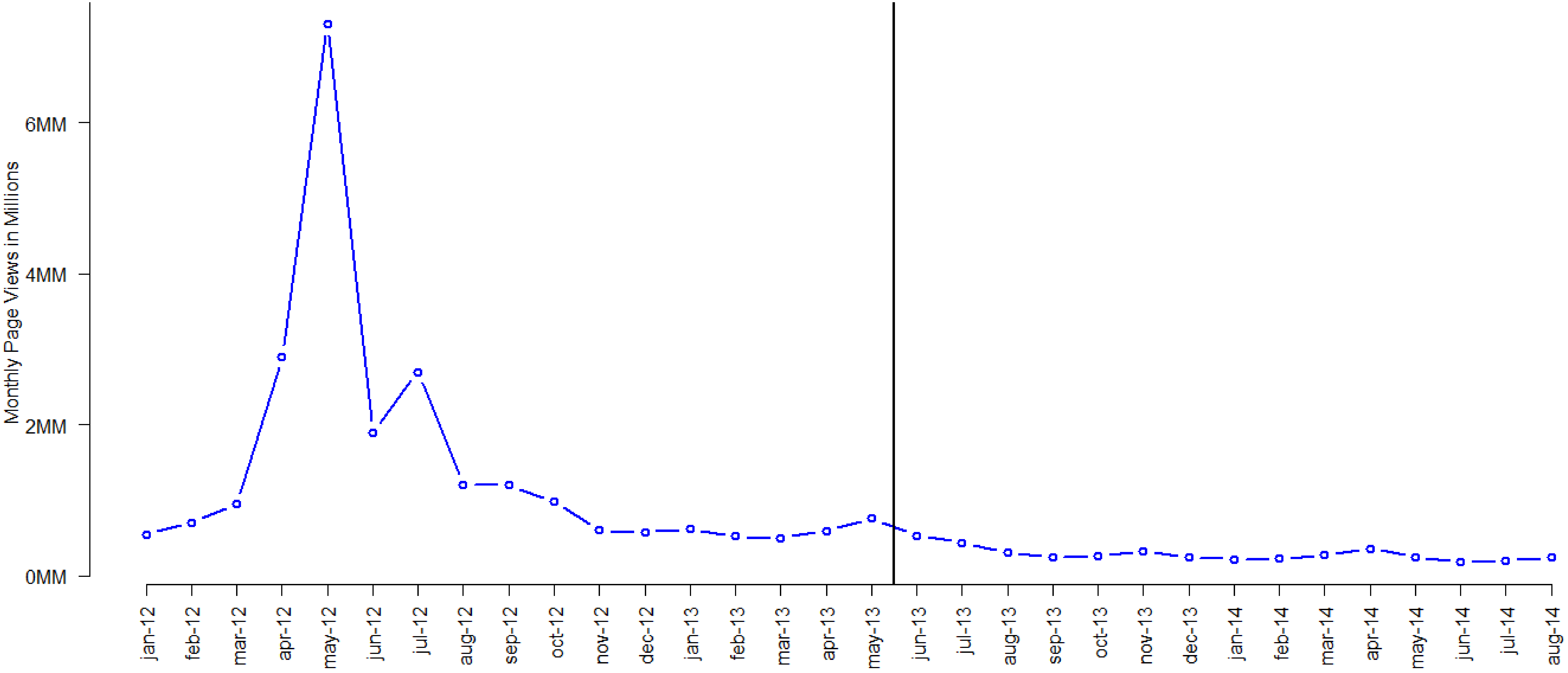


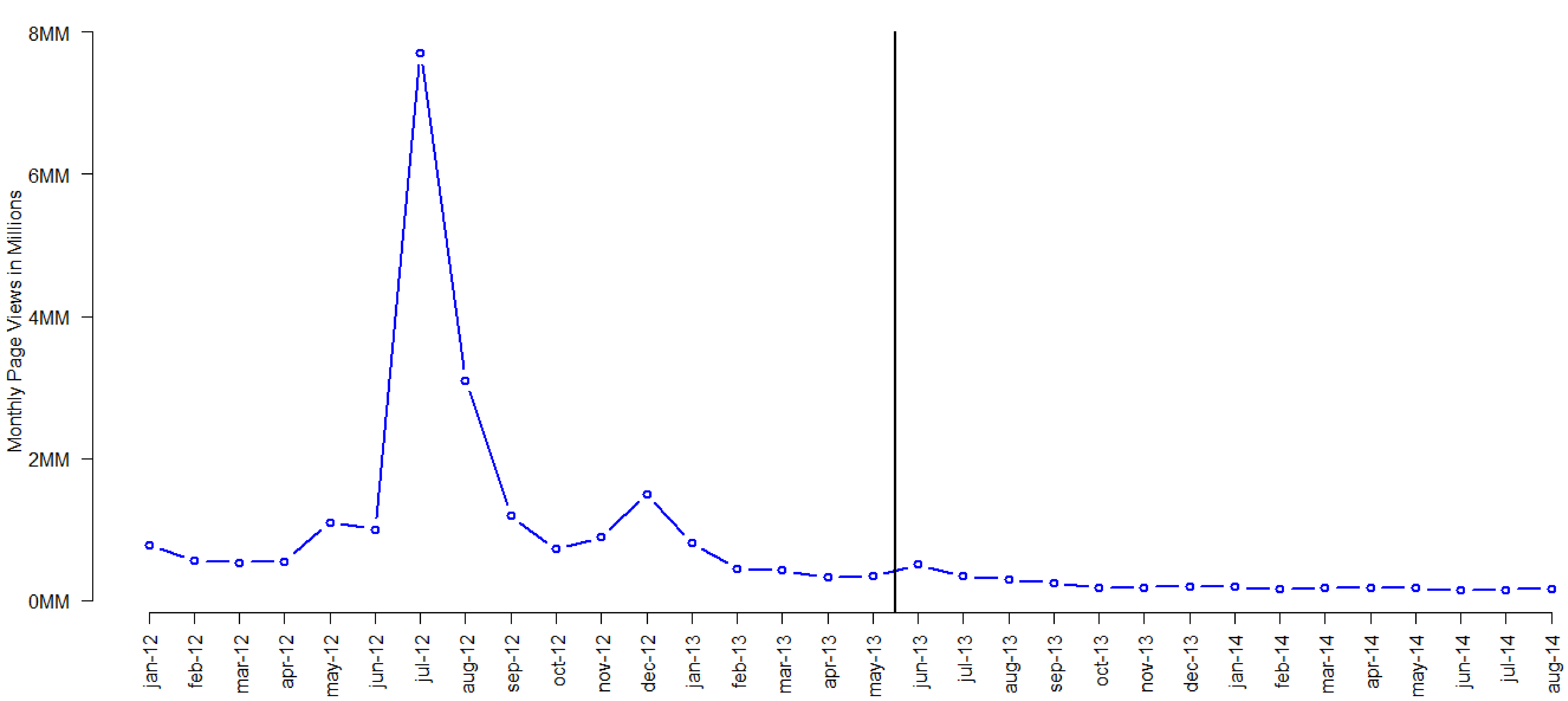

Popular: Page Views for one_direction
Monthly Page Views in Millions
3.5MM
3MM
2.5MM
2MM
1.5MM
1MM
0.5MM
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

# Popular: Page Views for online_shopping



# Popular: Page Views for the_avengers_2012_film




Popular: Page Views for the_dark_knight_rises
Monthly Page Views in Millions
8MM
6MM
4MM
2MM
0MM
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
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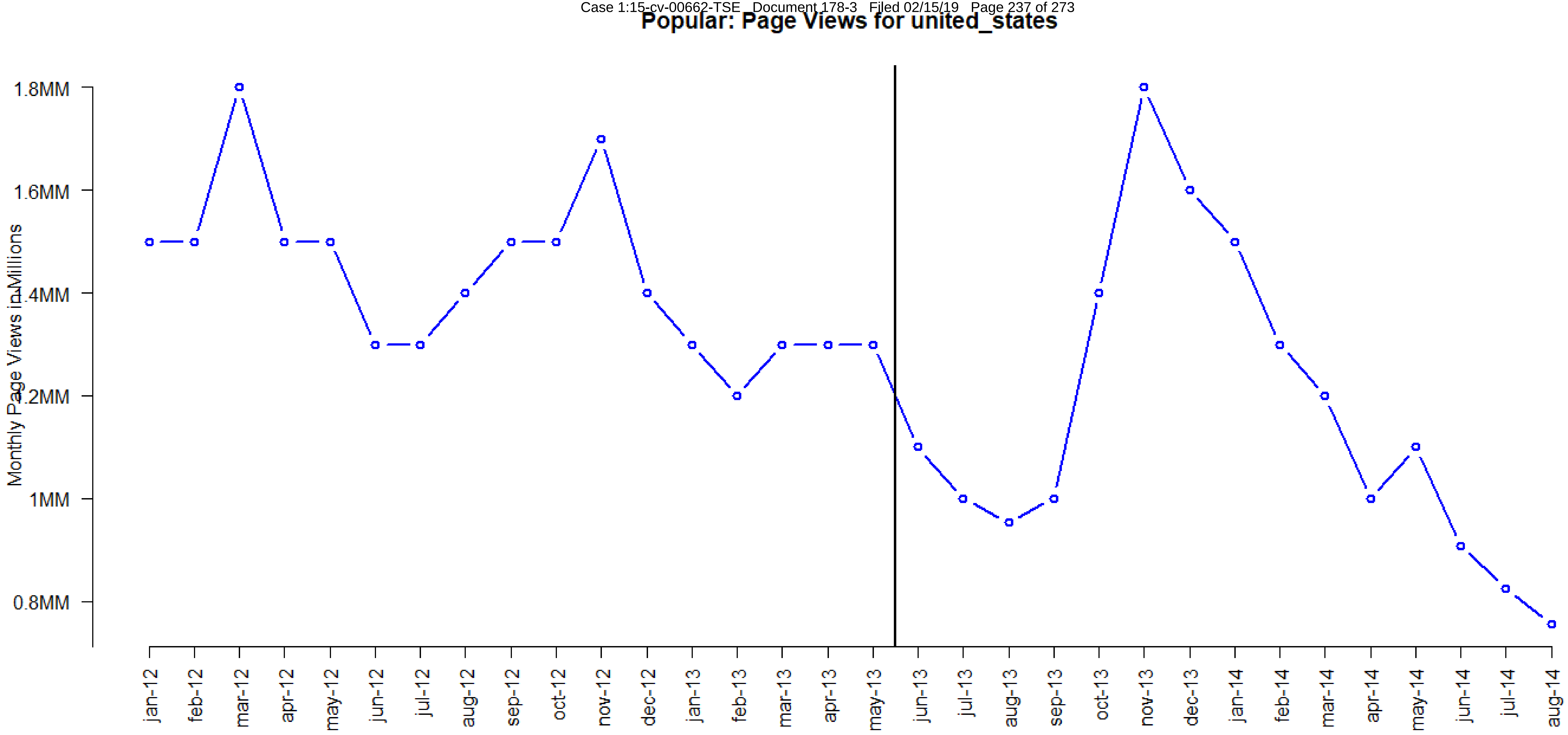
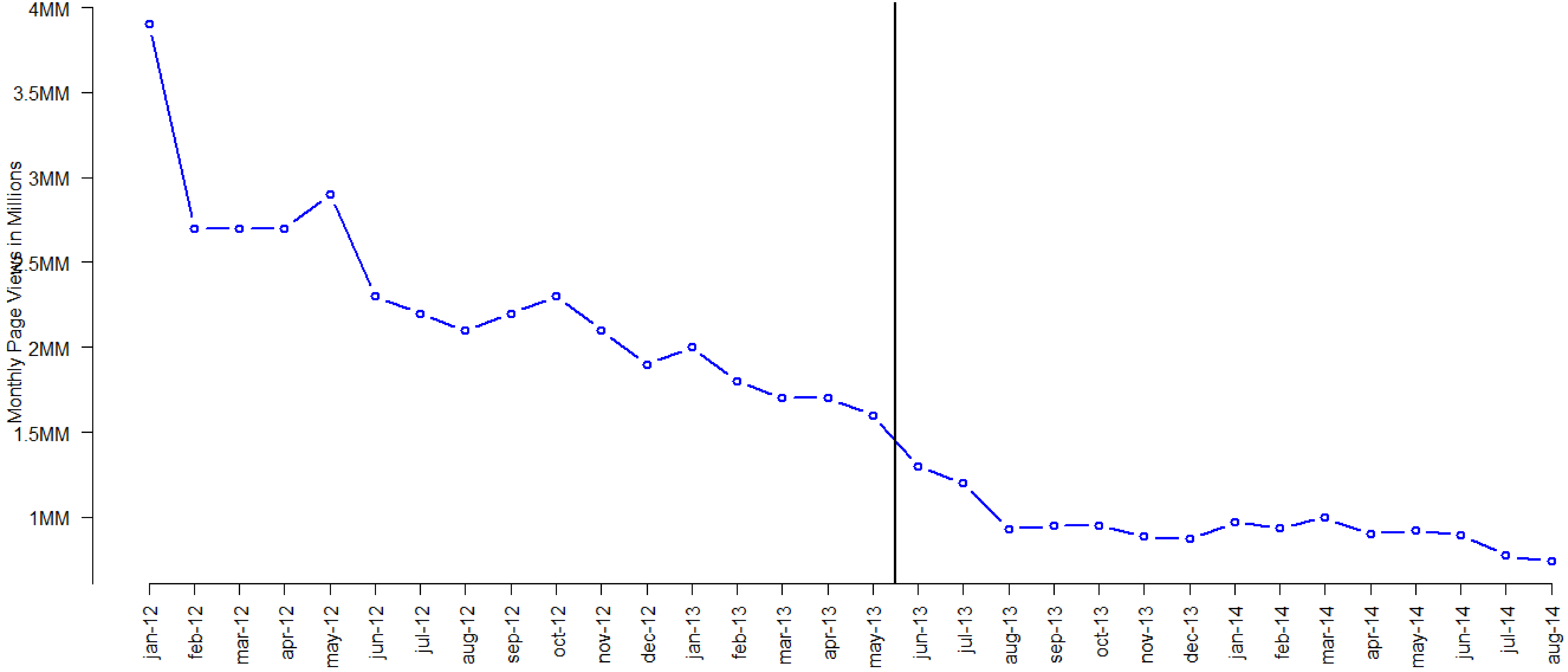
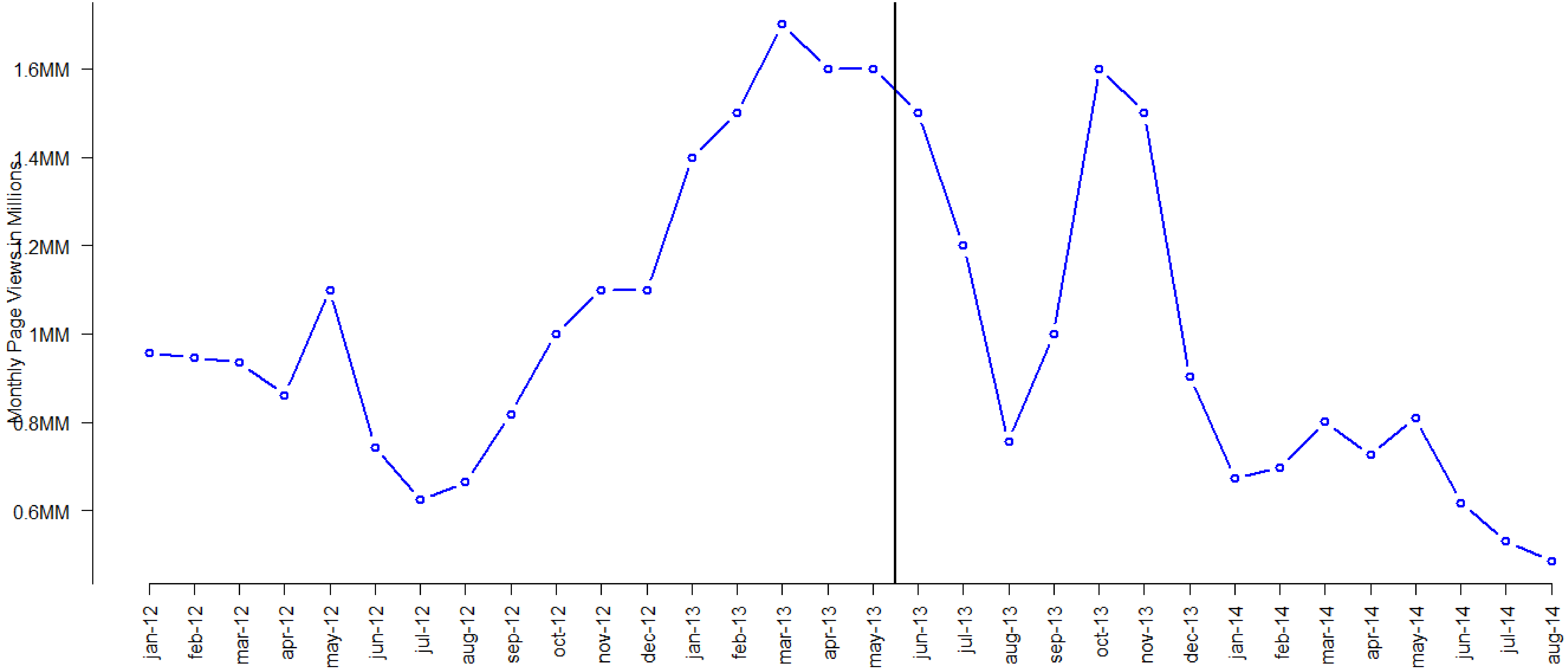
jun-14
jul-14
aug-14

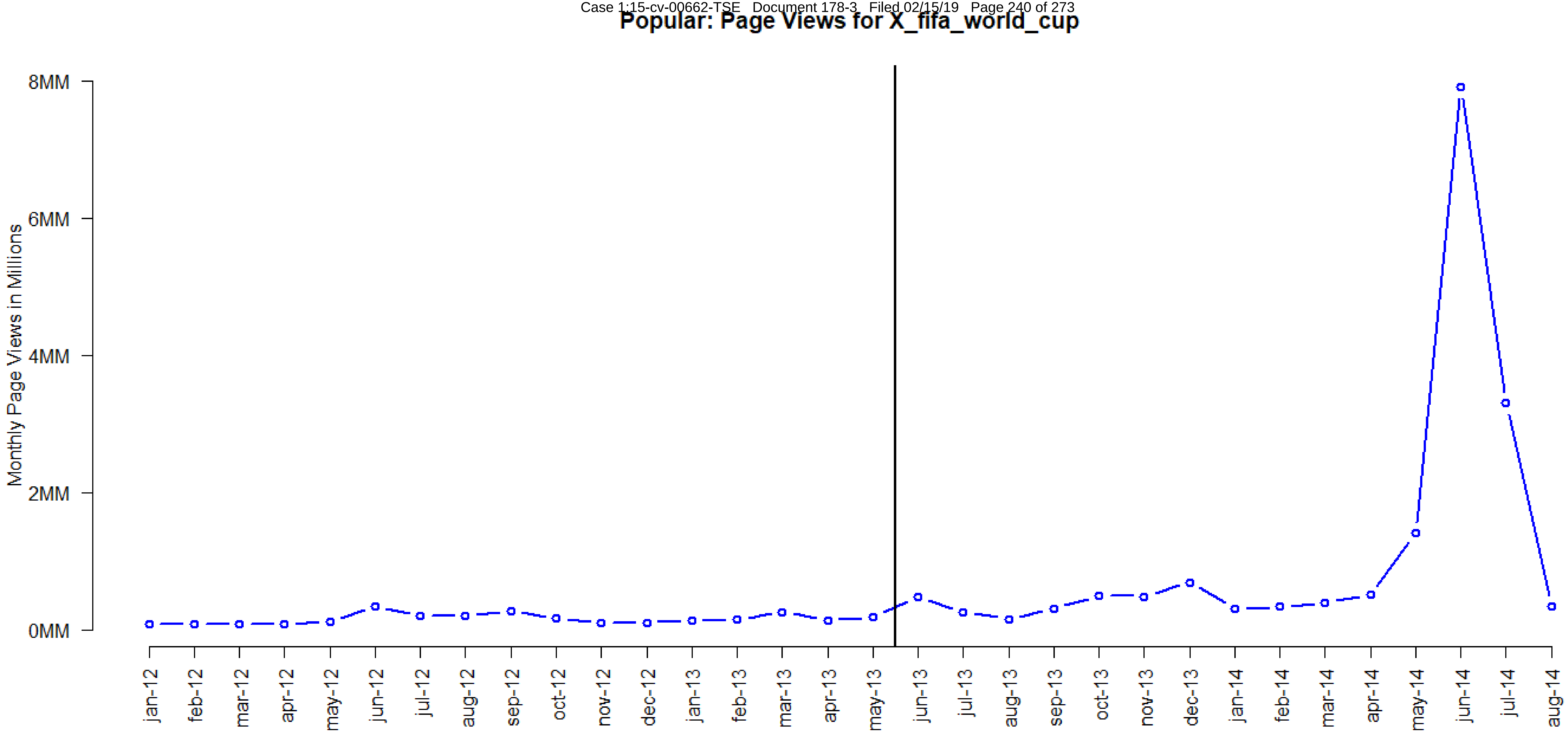

Popular: Page Views for united_states
Monthly Page Views in Millions
1.8MM
1.6MM
1.4MM
1.2MM
1MM
0.8MM
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

# Popular: Page Views for wiki



## Popular: Page Views for world_war_ii




Popular: Page Views for X_fifa_world_cup
Monthly Page Views in Millions
8MM
6MM
4MM
2MM
0MM
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
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jan-13
feb-13
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jul-13
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sep-13
oct-13
nov-13
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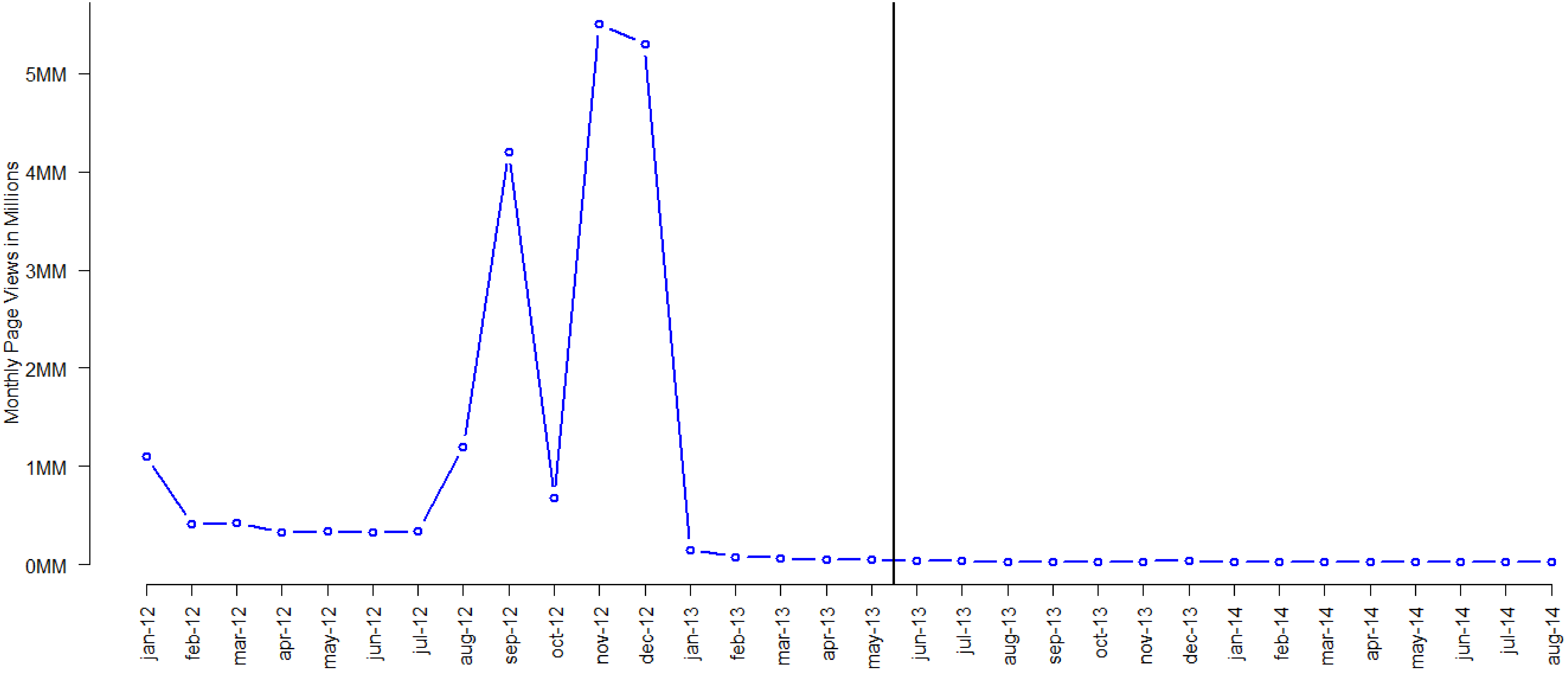
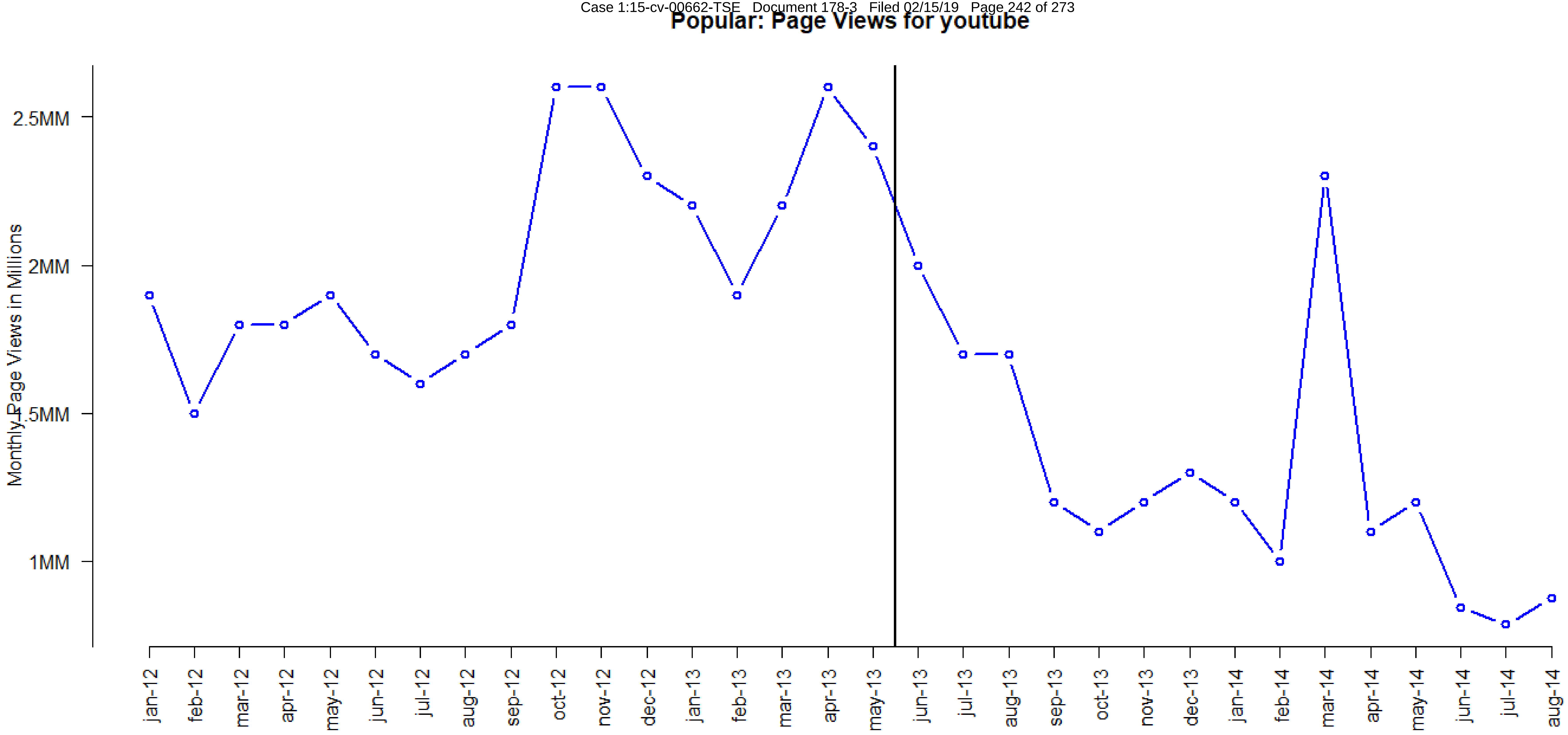
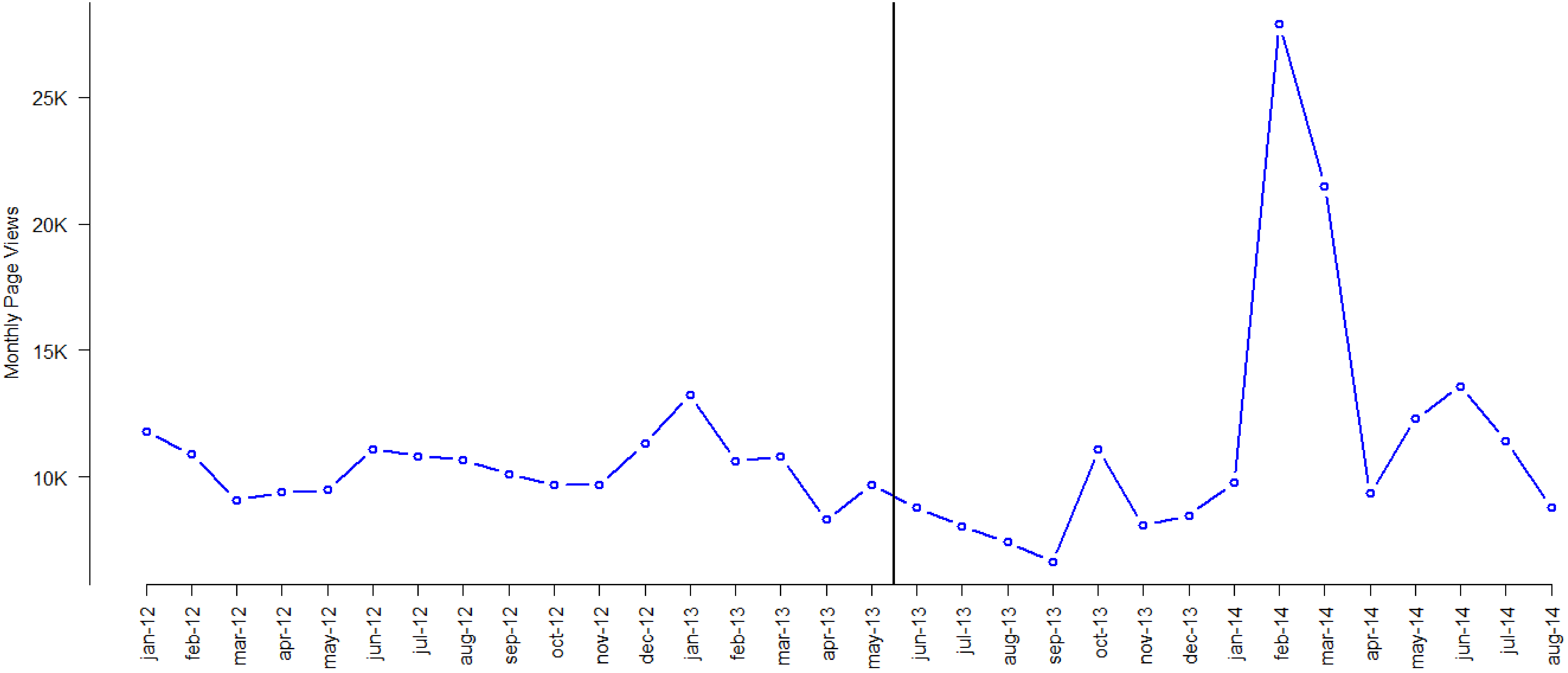
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

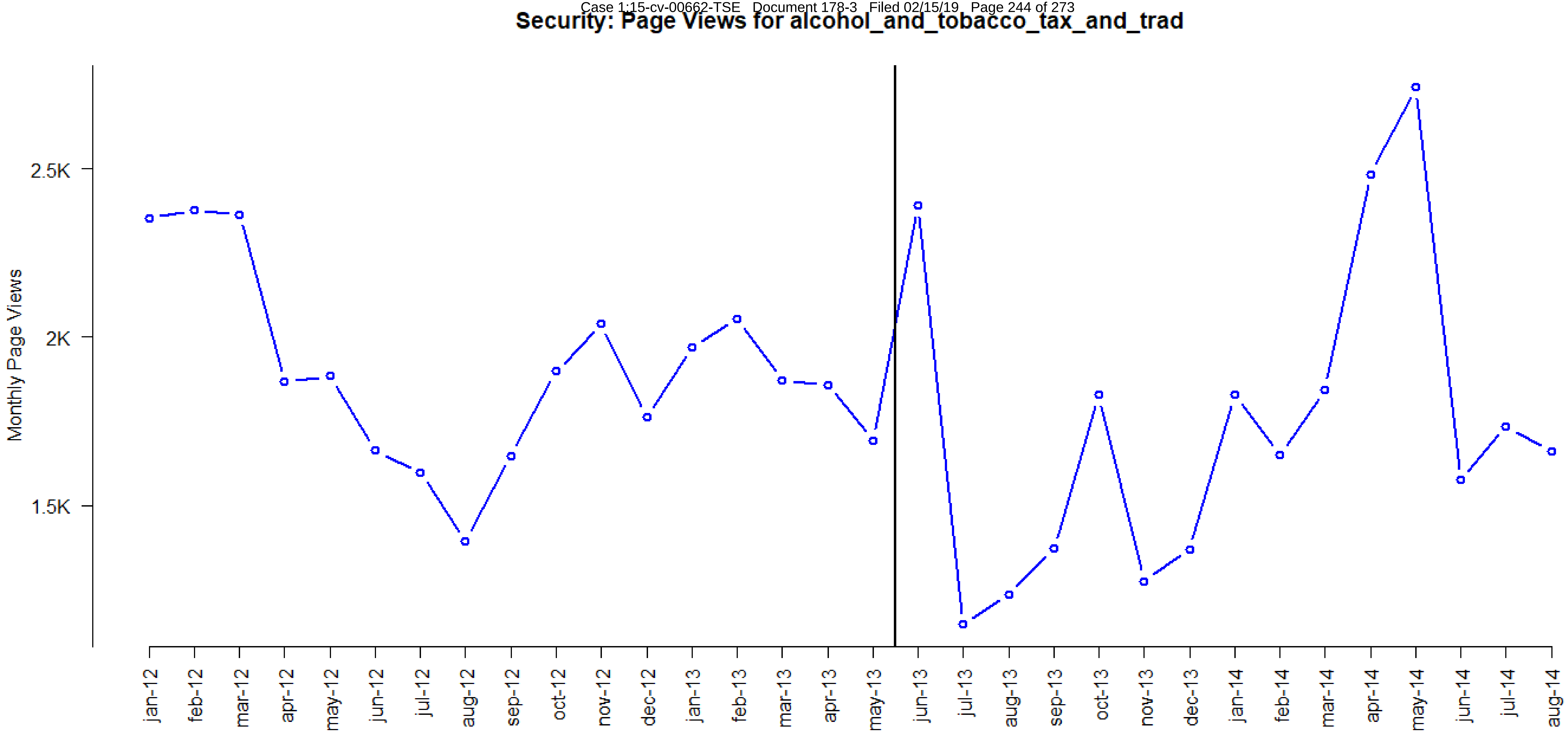
# Popular: Page Views for X_phenomena




Popular: Page Views for youtube
Monthly Page Views in Millions
2.5MM
2MM
1.5MM
1MM
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

## Security: Page Views for air_marshals




Security: Page Views for alcohol_and_tobacco_tax_and_trad
Monthly Page Views
2.5K
2K
1.5K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
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mar-13
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may-13
jun-13
jul-13
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sep-13
oct-13
nov-13
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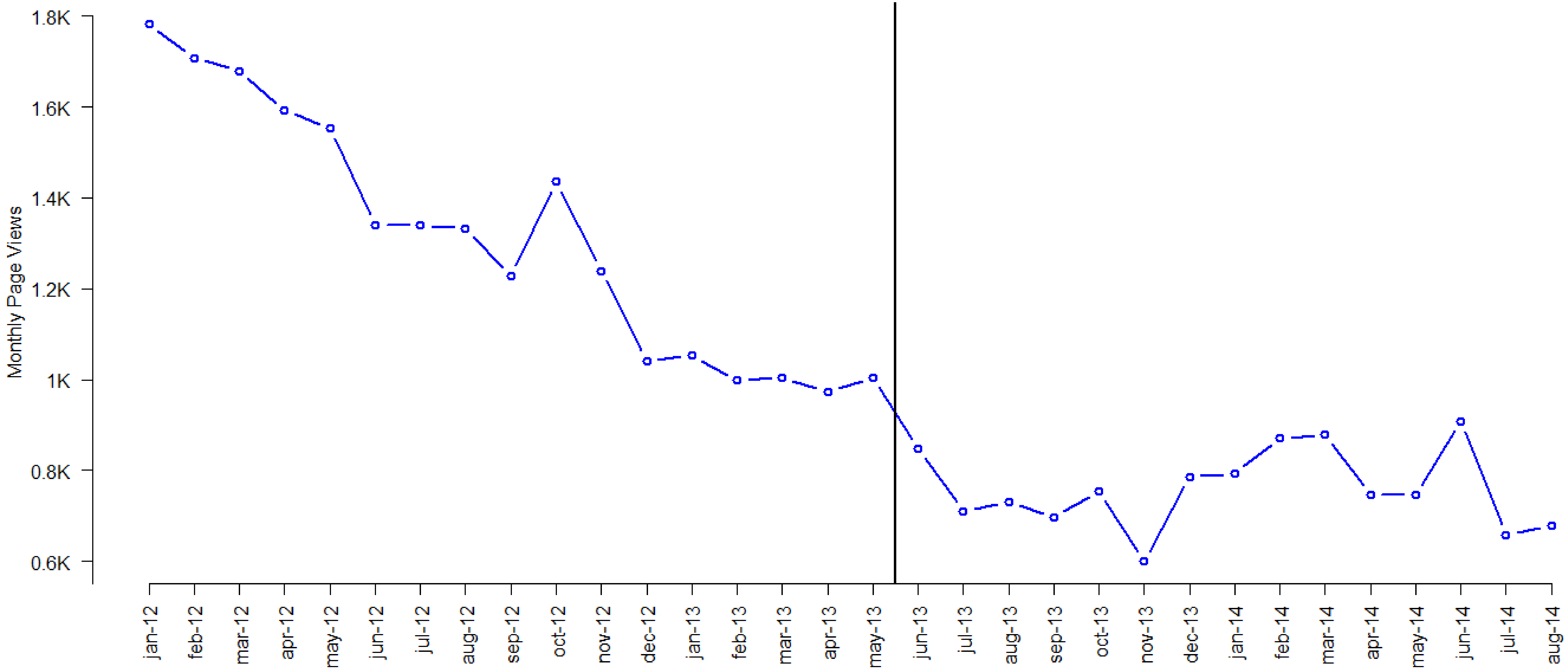
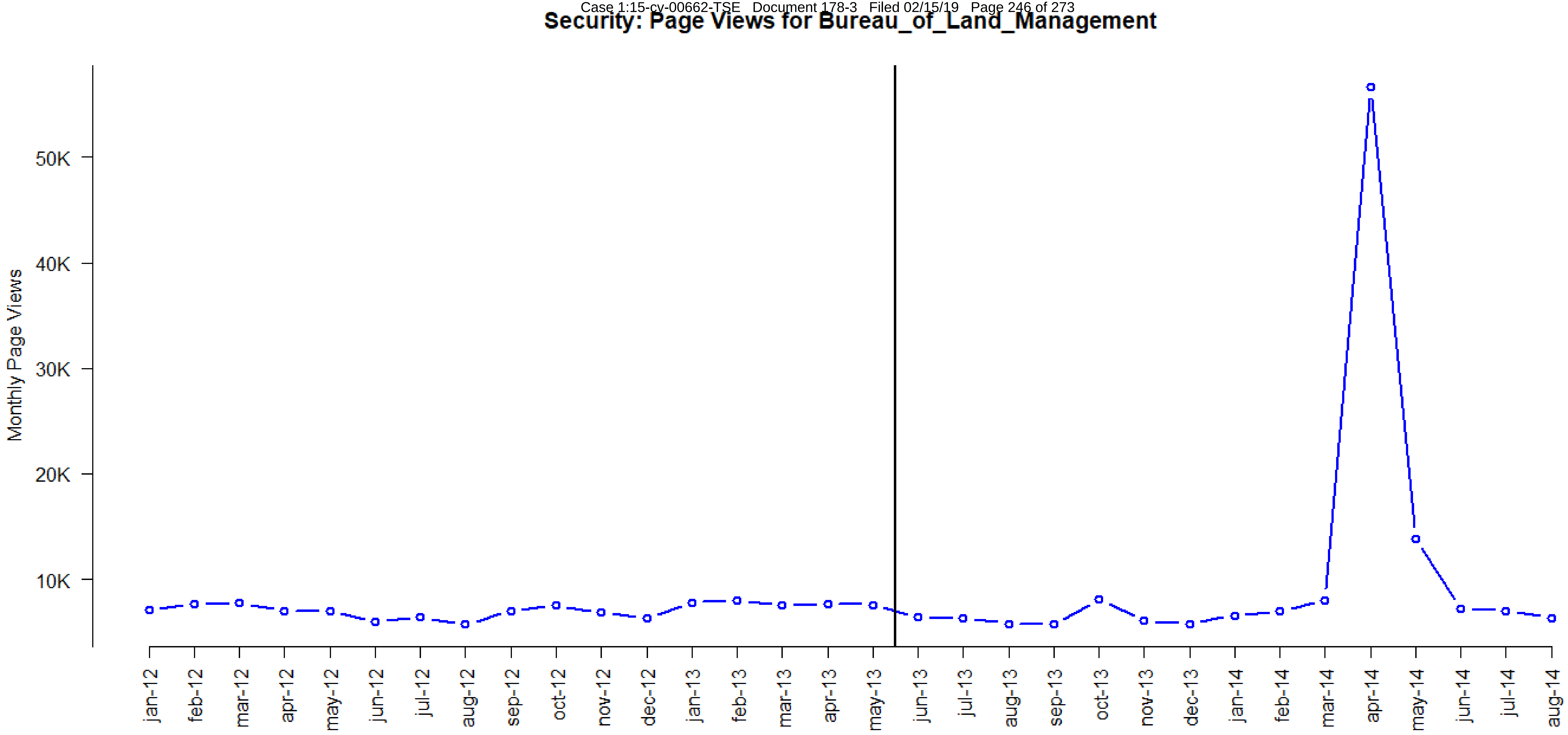
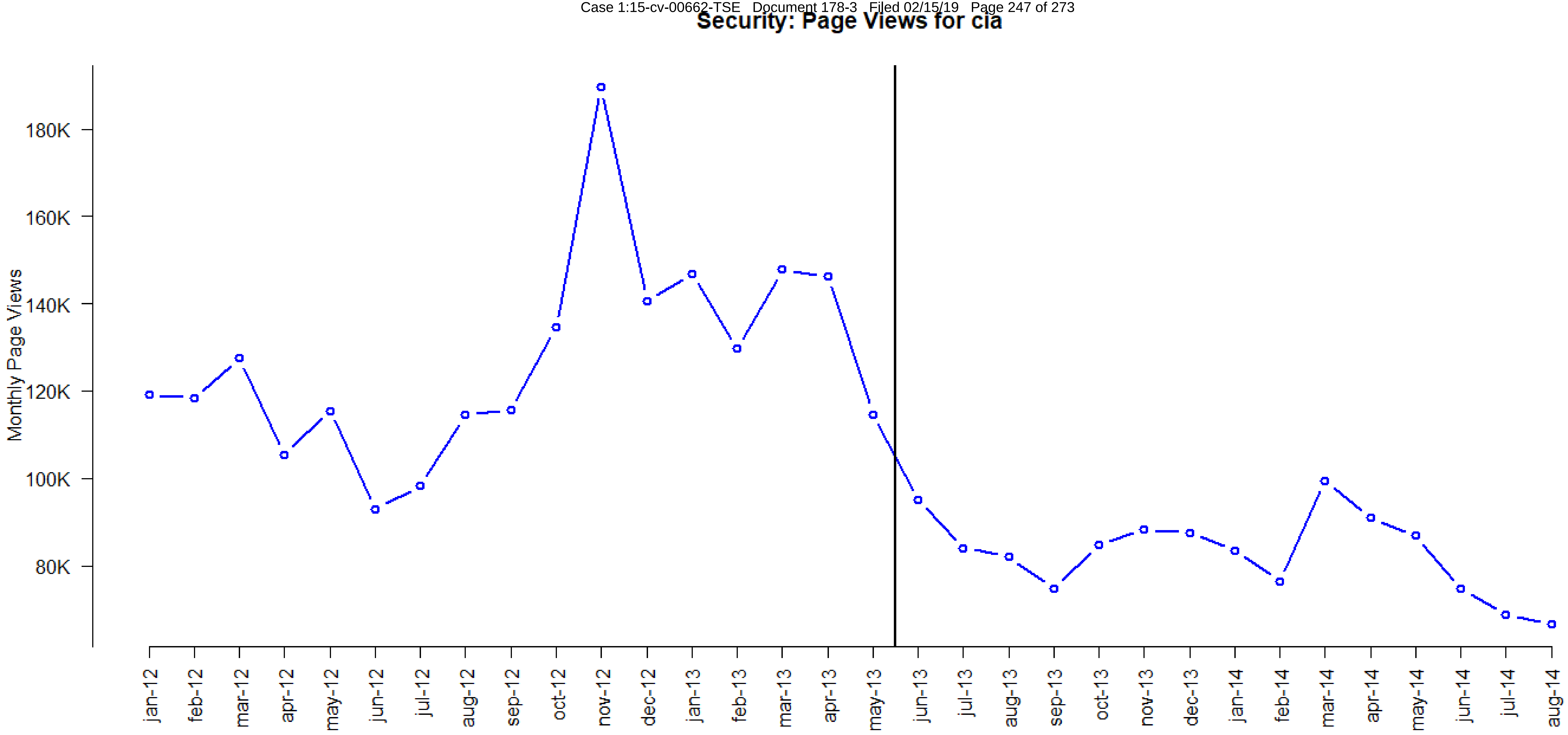
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

# Security: Page Views for border_patrol




Security: Page Views for Bureau_of_Land_Management
Monthly Page Views
50K
40K
30K
20K
10K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14


Security: Page Views for cia
Monthly Page Views
180K
160K
140K
120K
100K
80K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
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mar-13
apr-13
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jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
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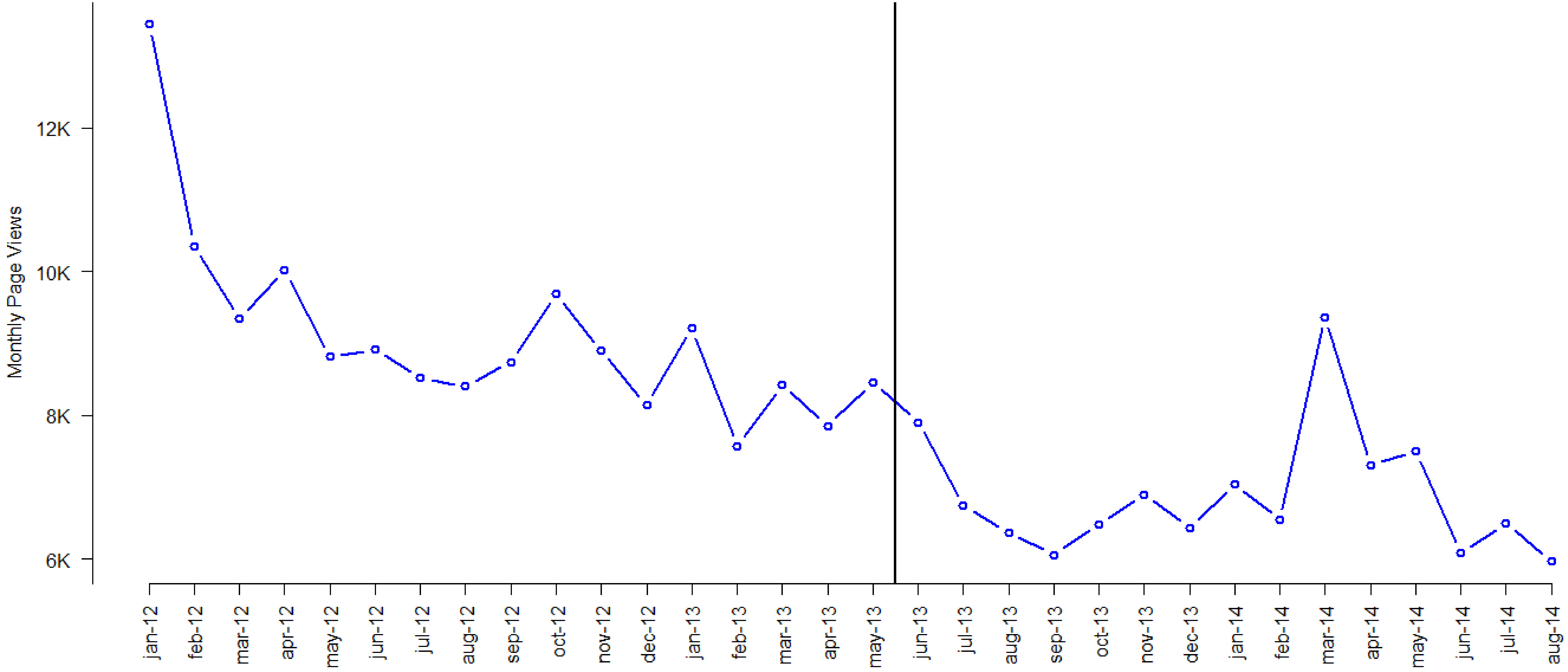
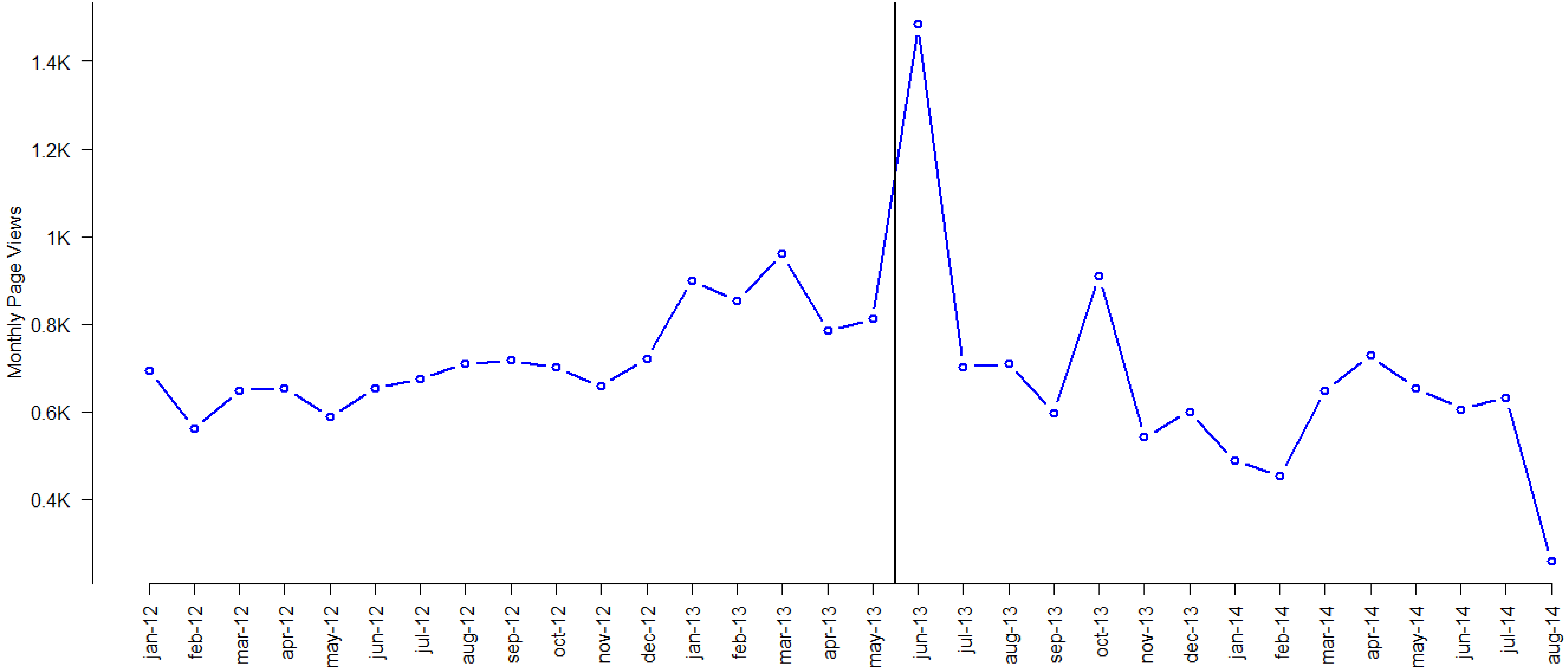
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14

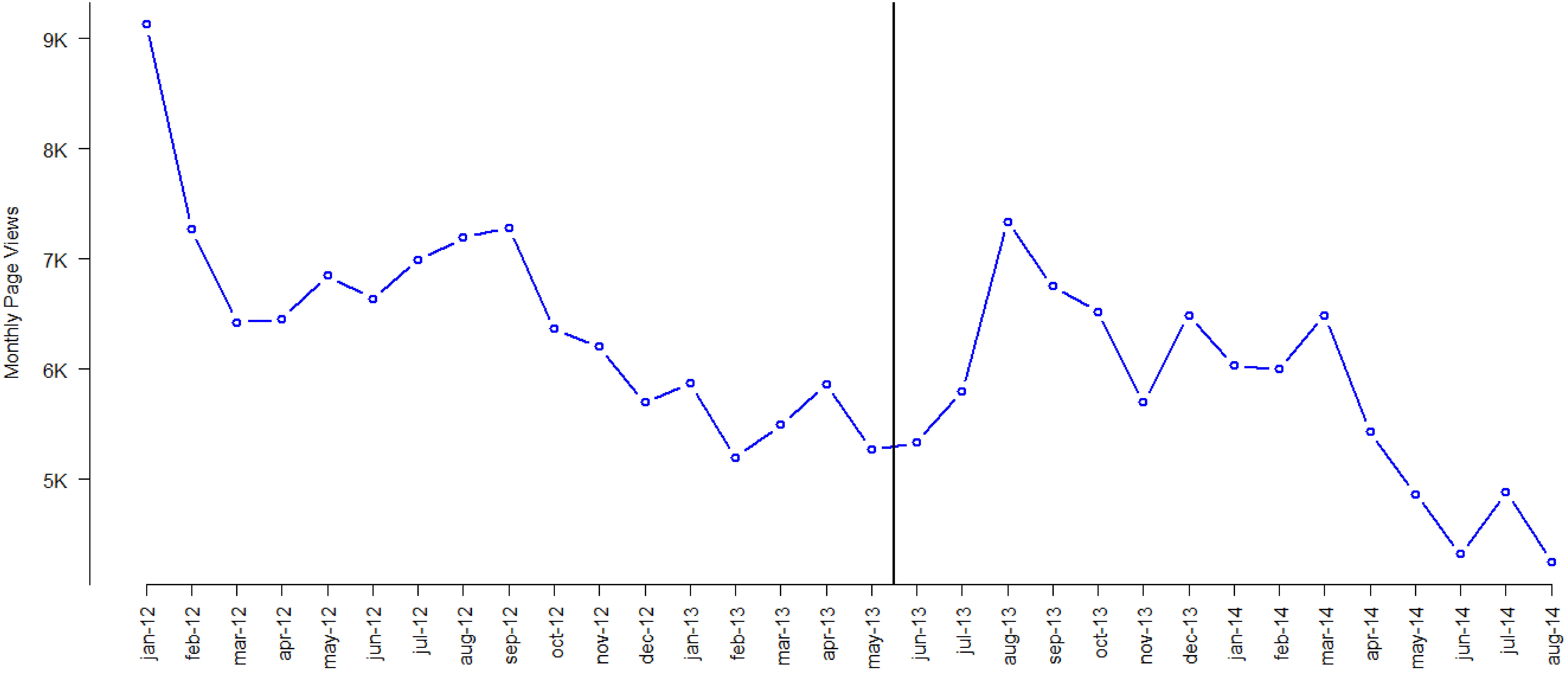
# Security: Page Views for coast_guard

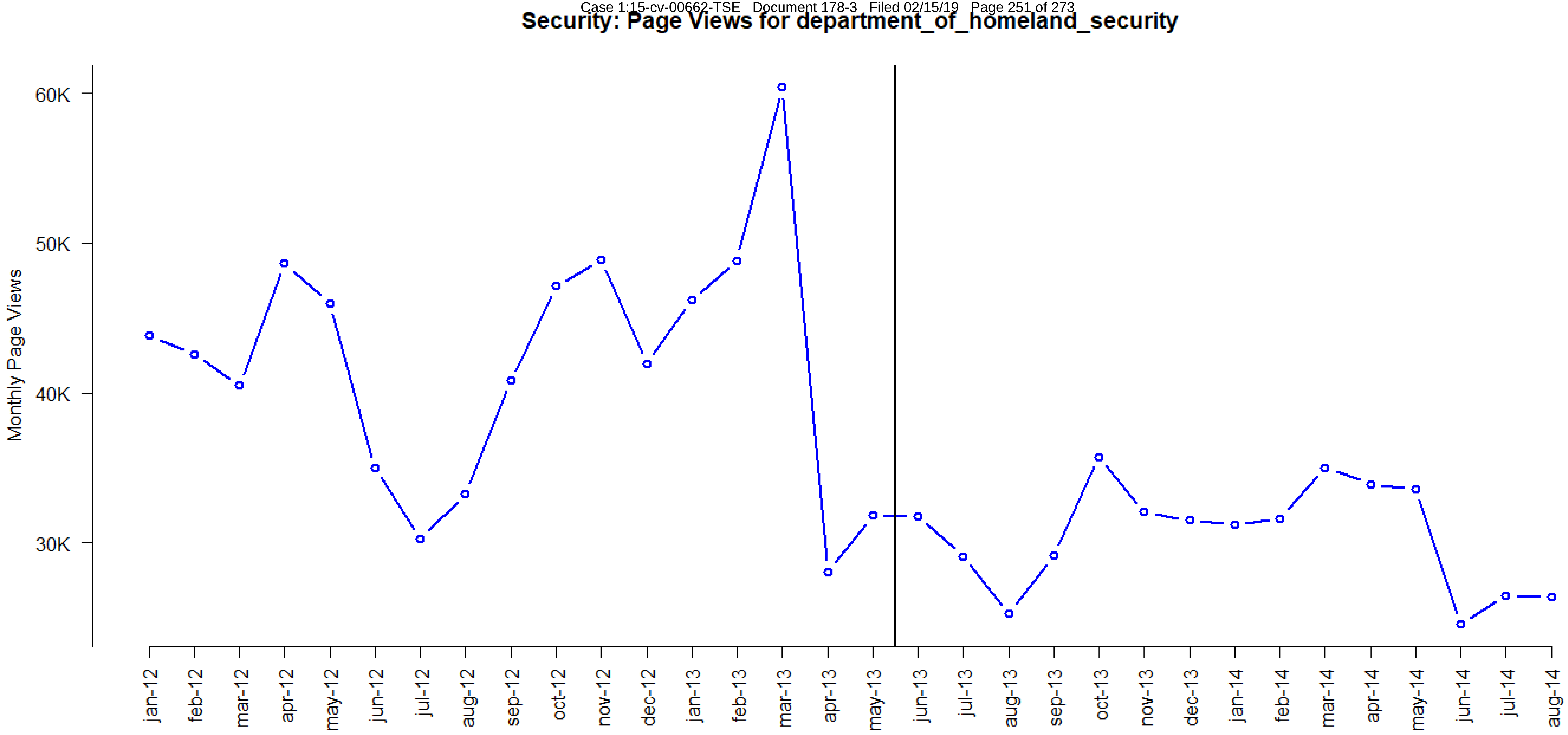


# Security: Page Views for customs_and_border_protection



# Security: Page Views for dea




Security: Page Views for department_of_homeland_security
Monthly Page Views
60K
50K
40K
30K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
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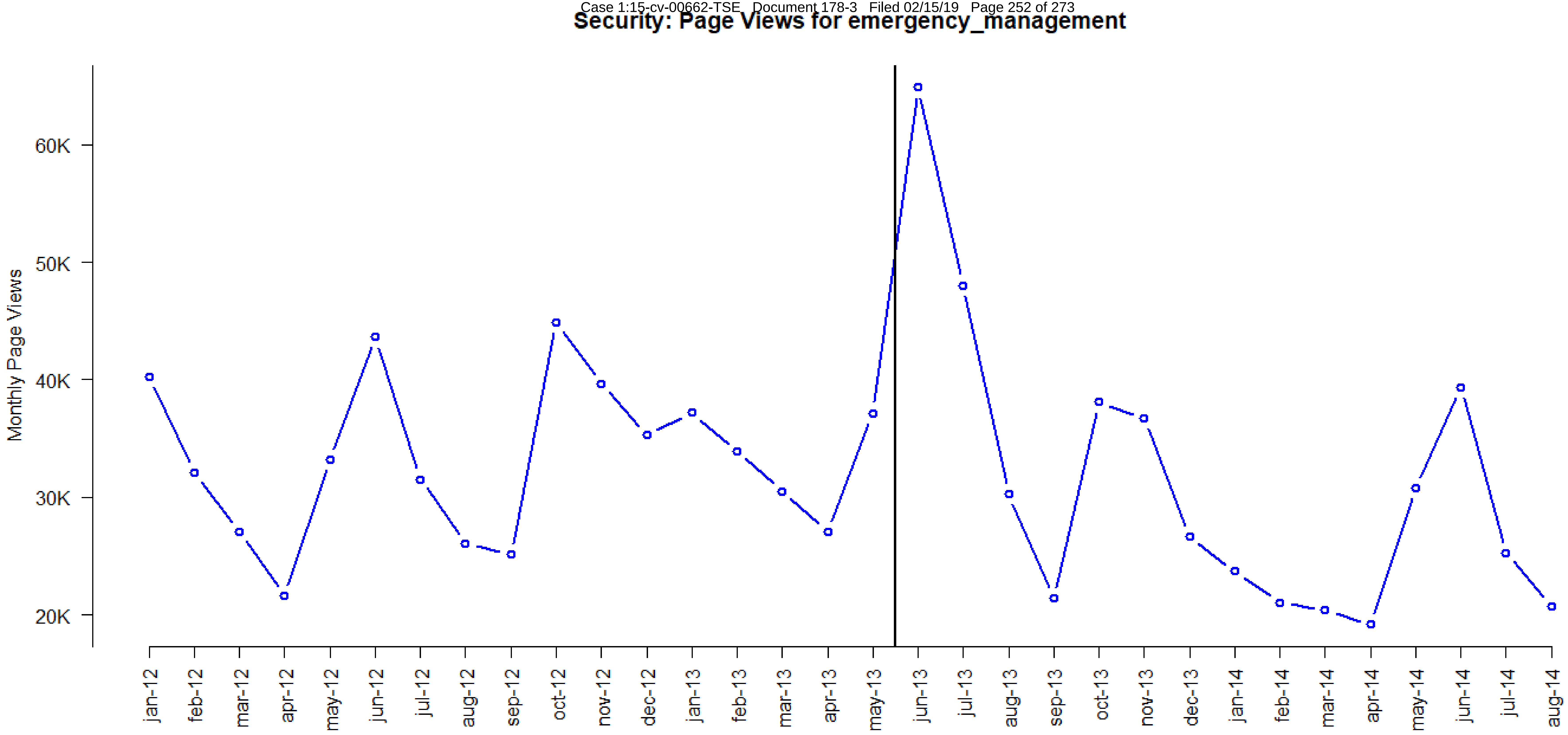
jun-14
jul-14
aug-14


Security: Page Views for emergency_management
Monthly Page Views
60K
50K
40K
30K
20K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
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aug-12
sep-12
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dec-12
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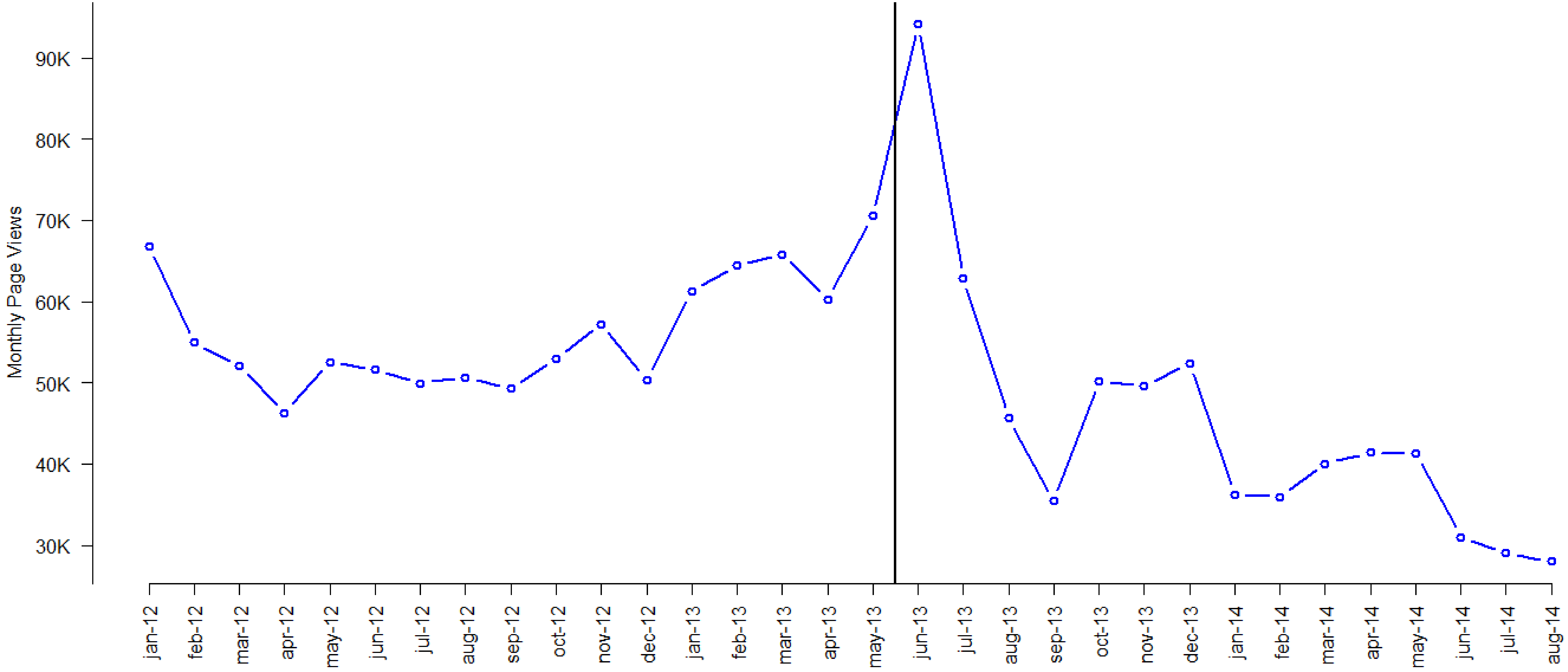
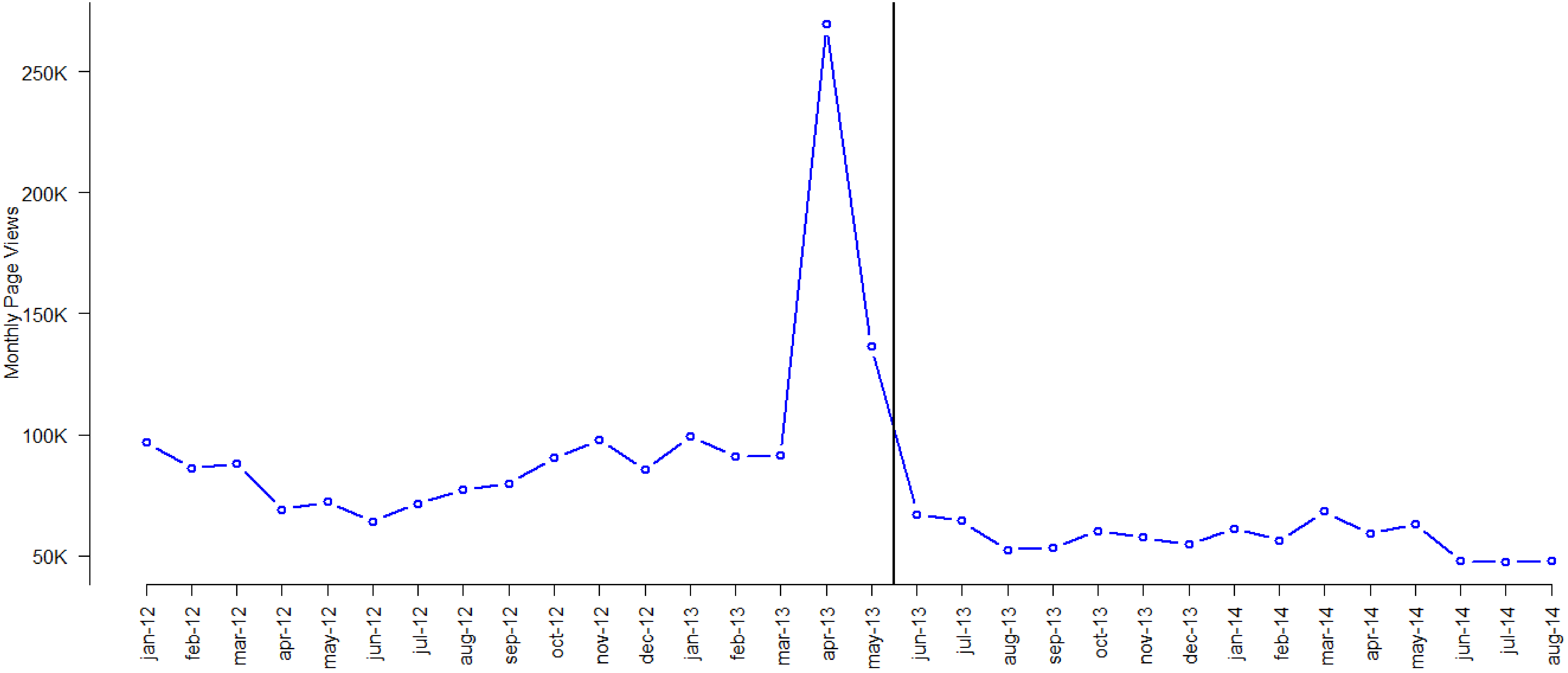
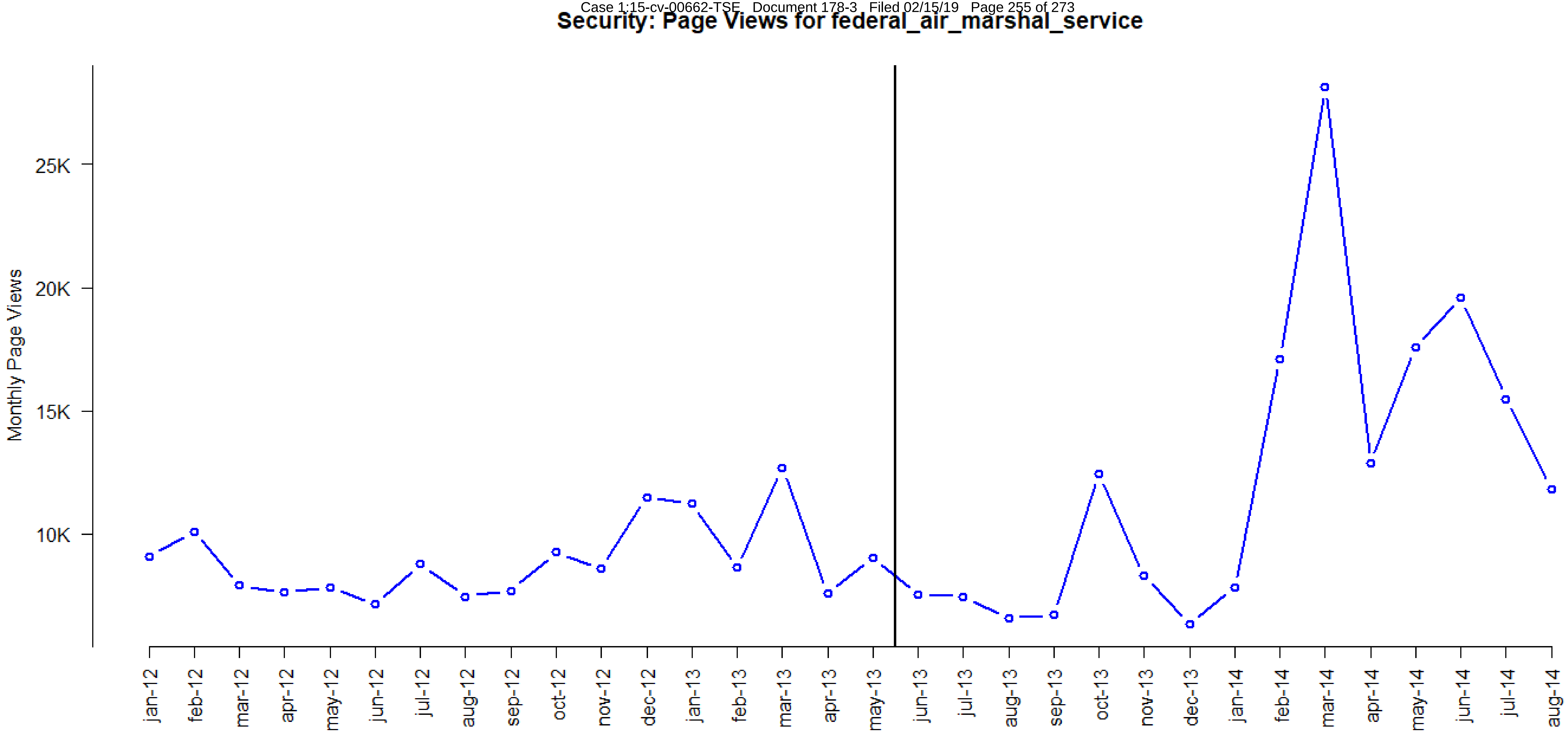
jul-14
aug-14

## Security: Page Views for espionage



# Security: Page Views for fbi




Security: Page Views for federal_air_marshal_service
Monthly Page Views
25K
20K
15K
10K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
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jan-13
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jul-13
aug-13
sep-13
oct-13
nov-13
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jan-14
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mar-14
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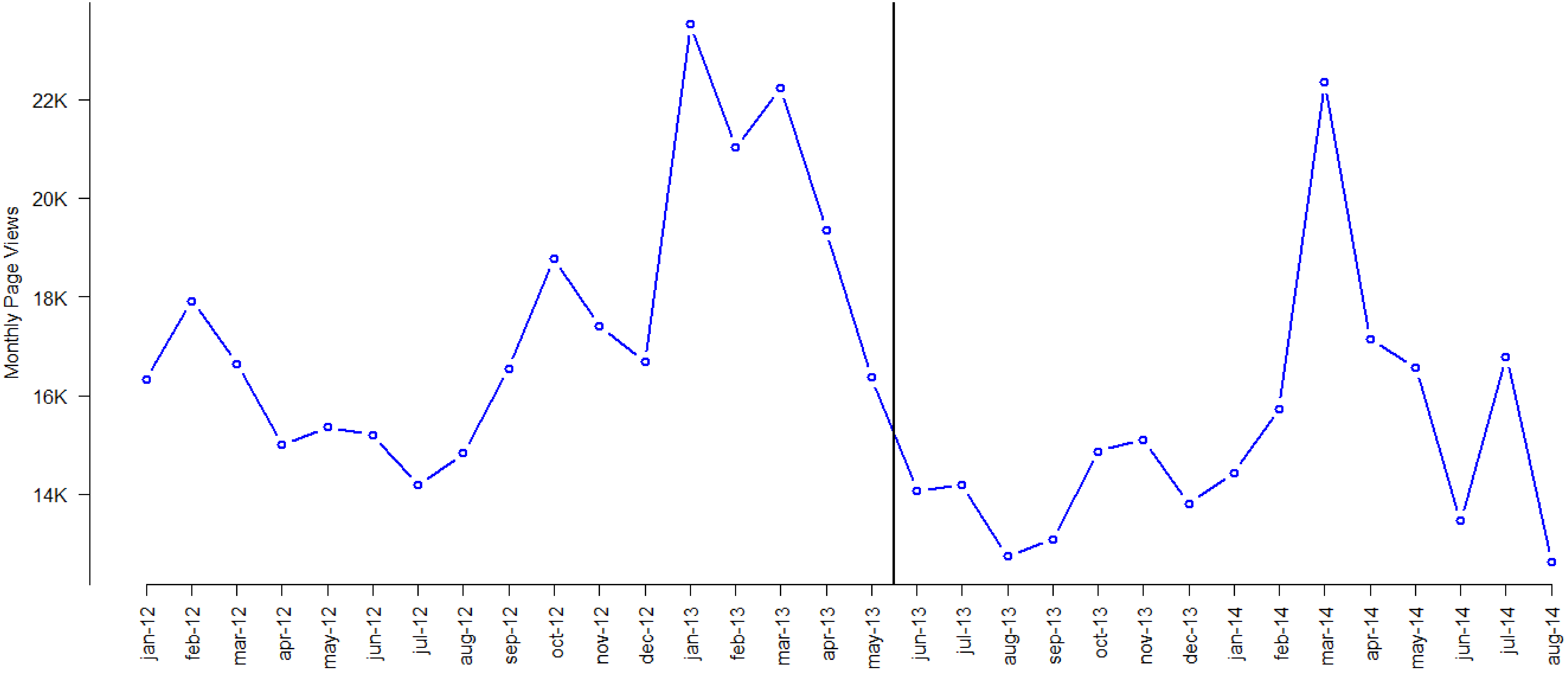
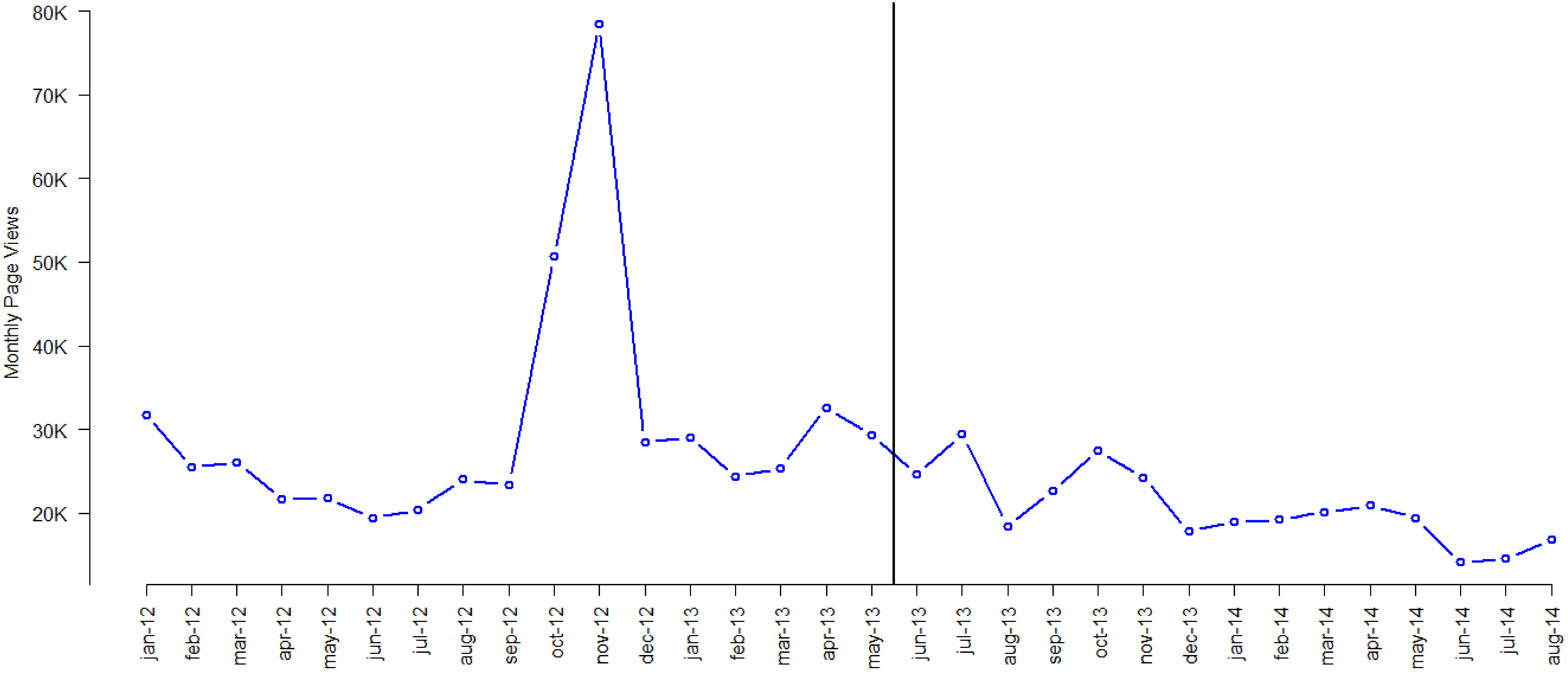
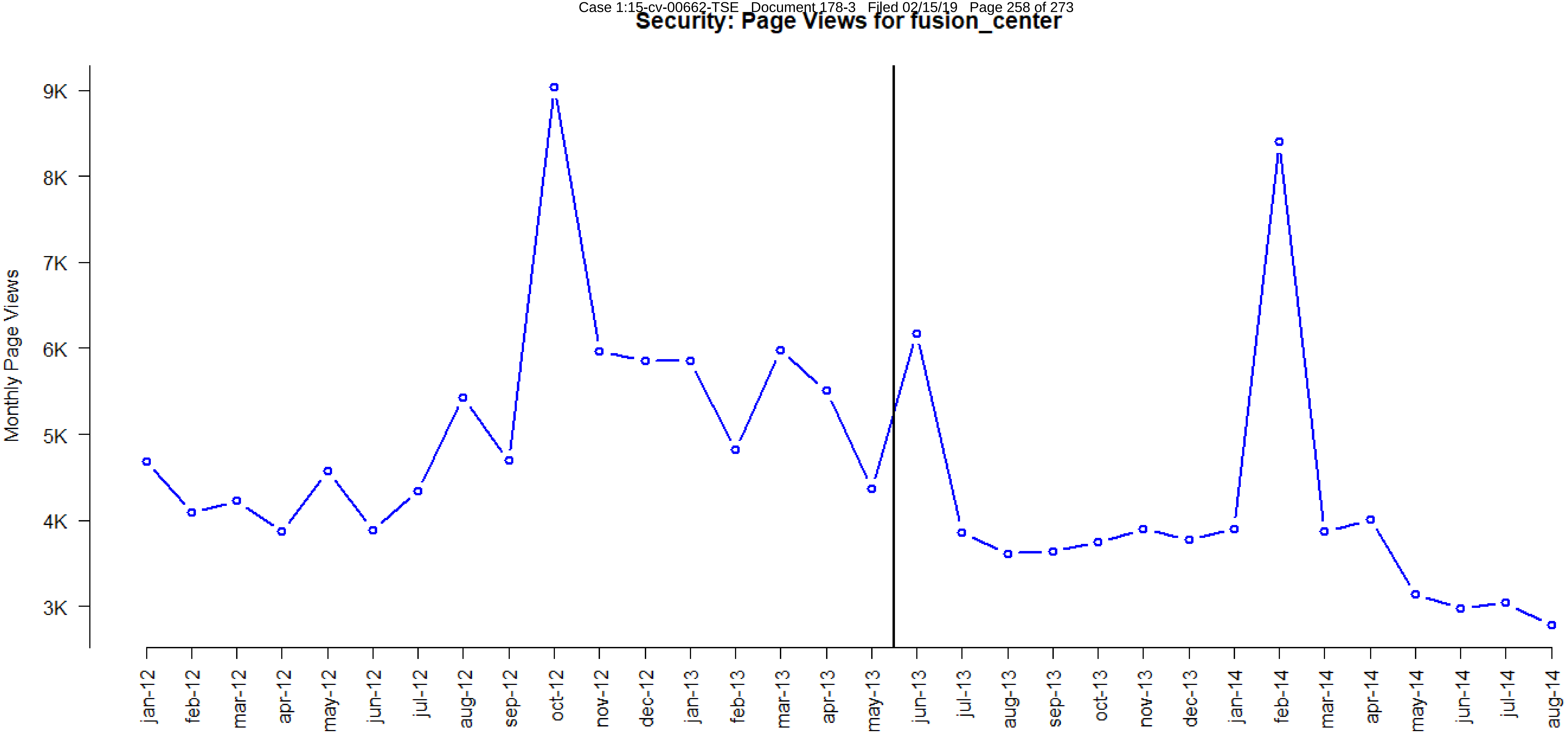
jun-14
jul-14
aug-14

# Security: Page Views for federal_aviation_administration



# Security: Page Views for federal_emergency_management_age




Security: Page Views for fusion_center
Monthly Page Views
9K
8K
7K
6K
5K
4K
3K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
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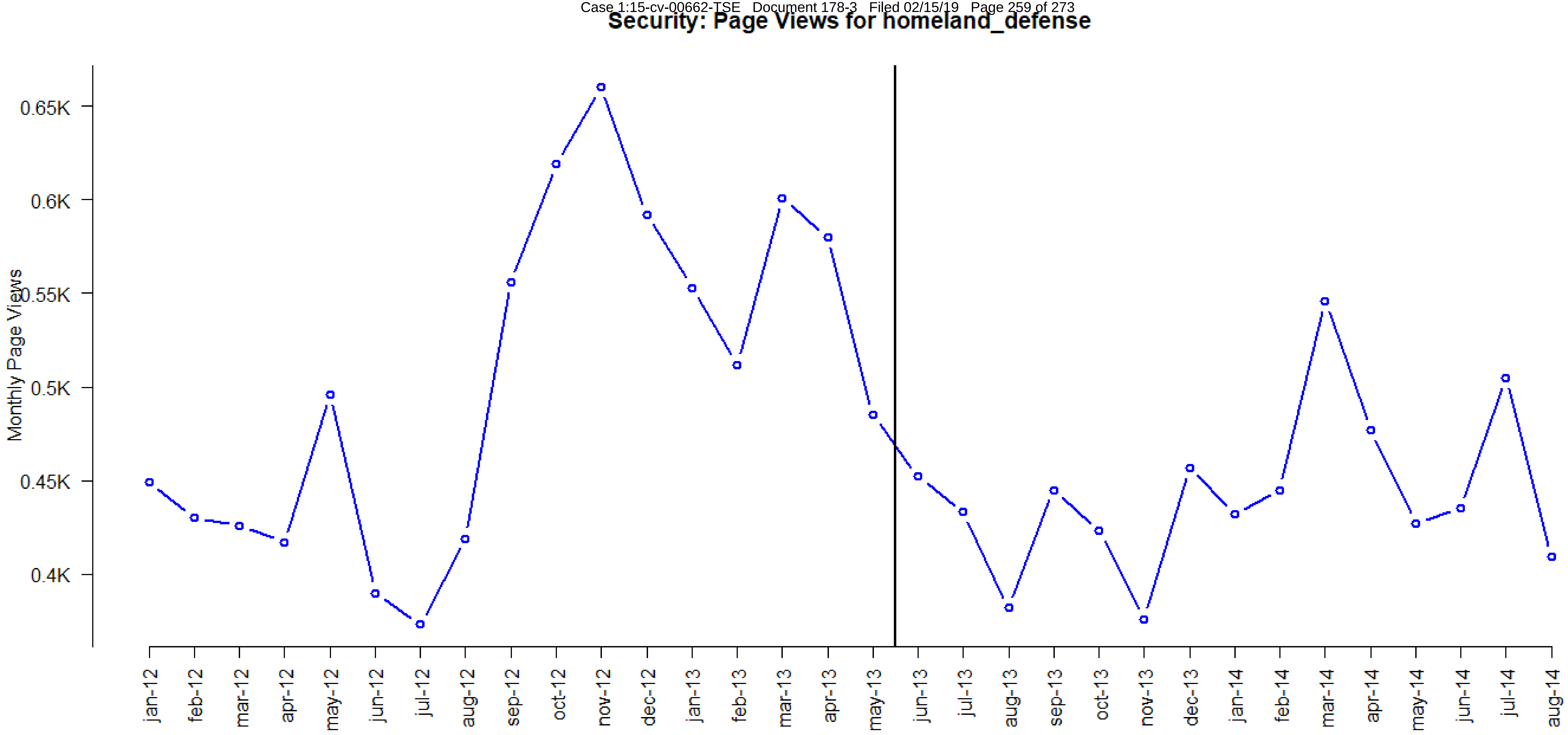
oct-13
nov-13
dec-13
jan-14
feb-14
mar-14
apr-14
may-14
jun-14
jul-14
aug-14


Security: Page Views for homeland_defense
Monthly Page Views
0.65K
0.6K
0.55K
0.5K
0.45K
0.4K
jan-12
feb-12
mar-12
apr-12
may-12
jun-12
jul-12
aug-12
sep-12
oct-12
nov-12
dec-12
jan-13
feb-13
mar-13
apr-13
may-13
jun-13
jul-13
aug-13
sep-13
oct-13
nov-13
dec-13
jan-14
feb-14
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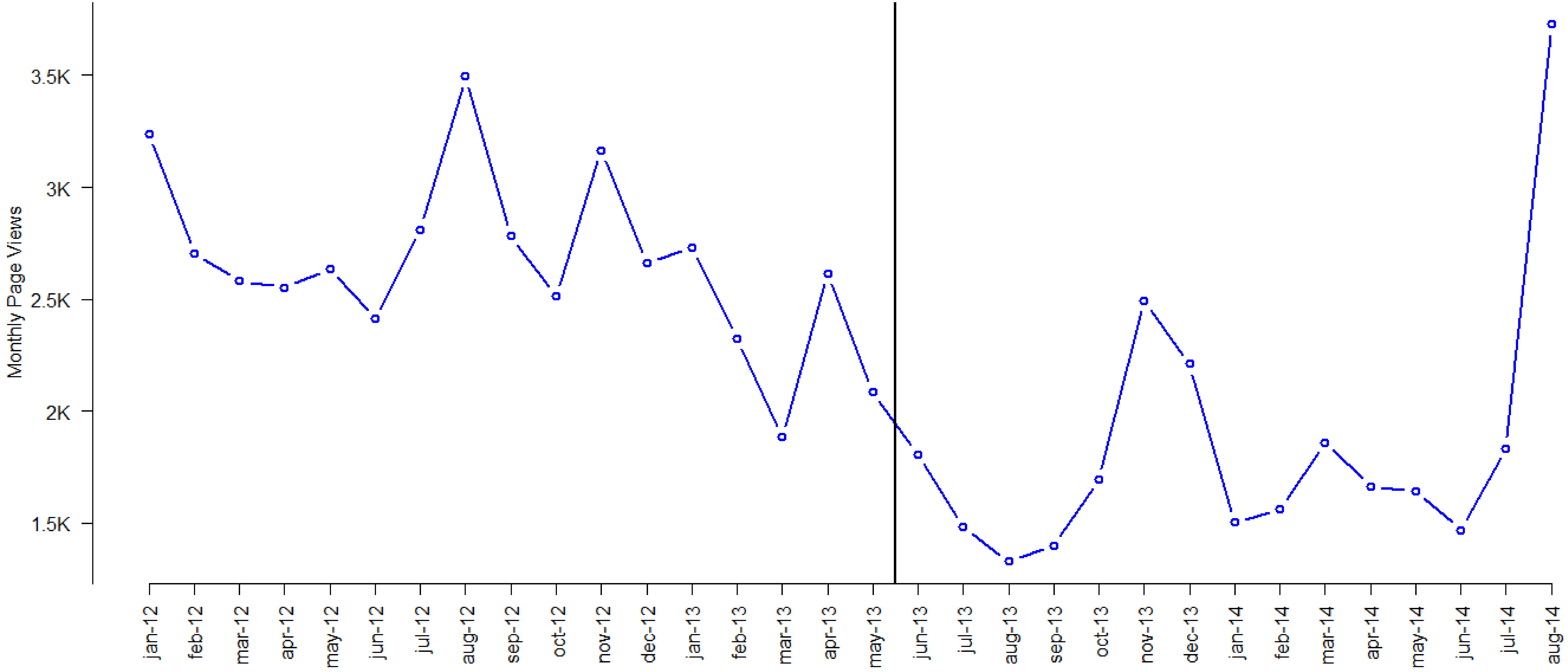
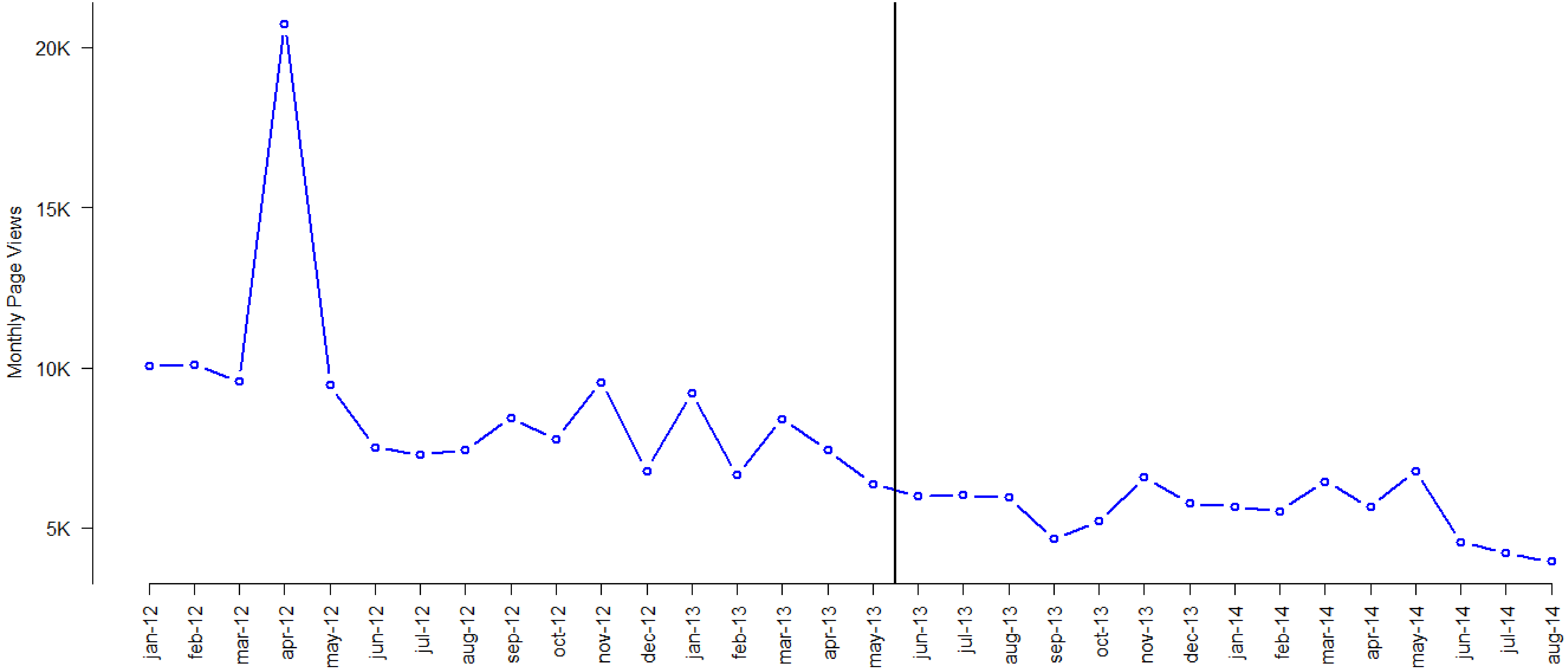
apr-14
may-14
jun-14
jul-14
aug-14

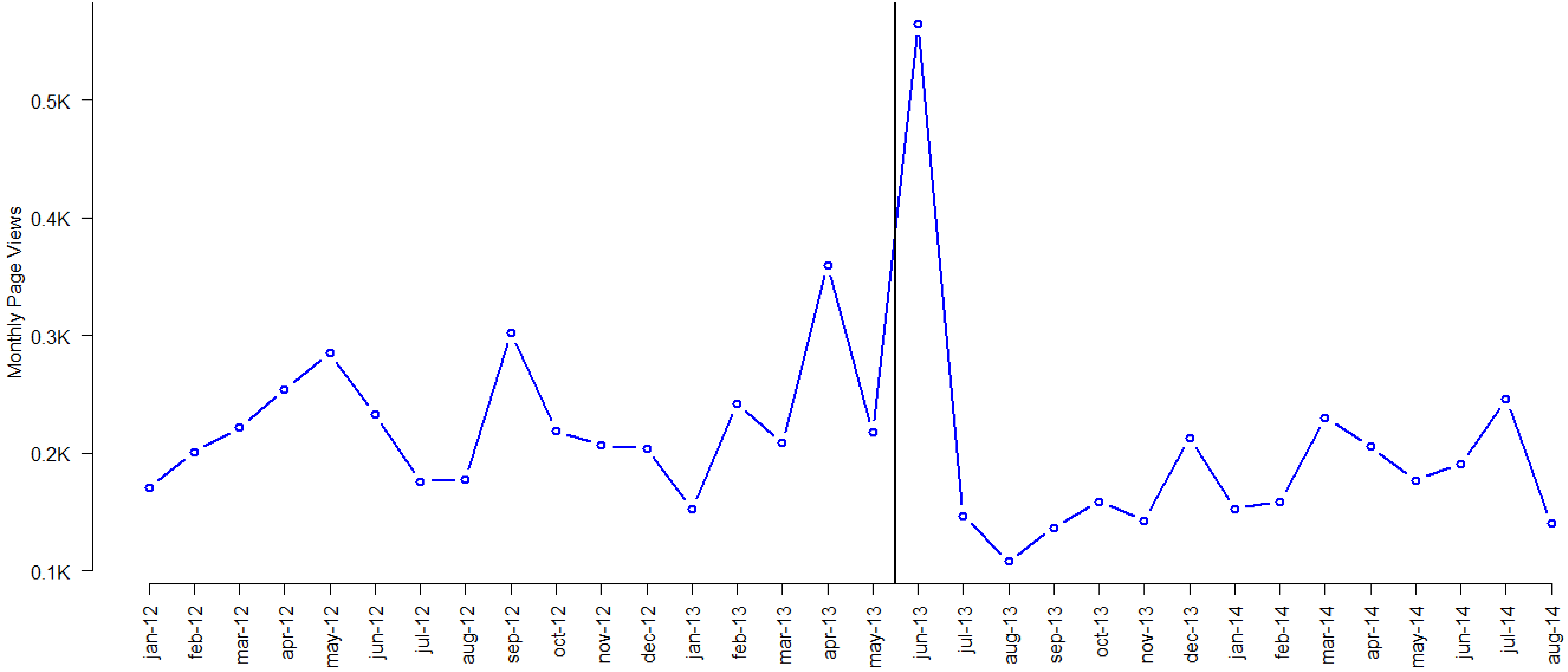
## Security: Page Views for national_guard



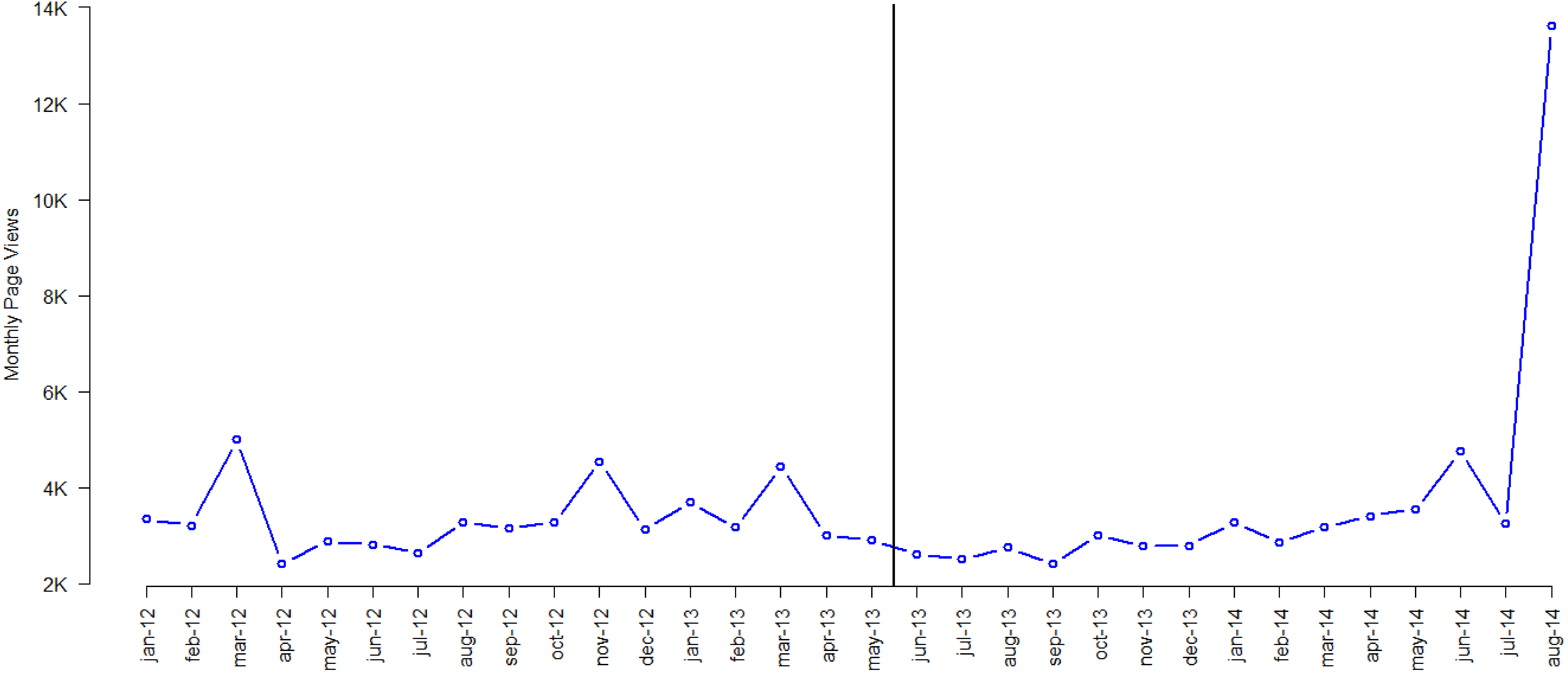
## Security: Page Views for secret_service



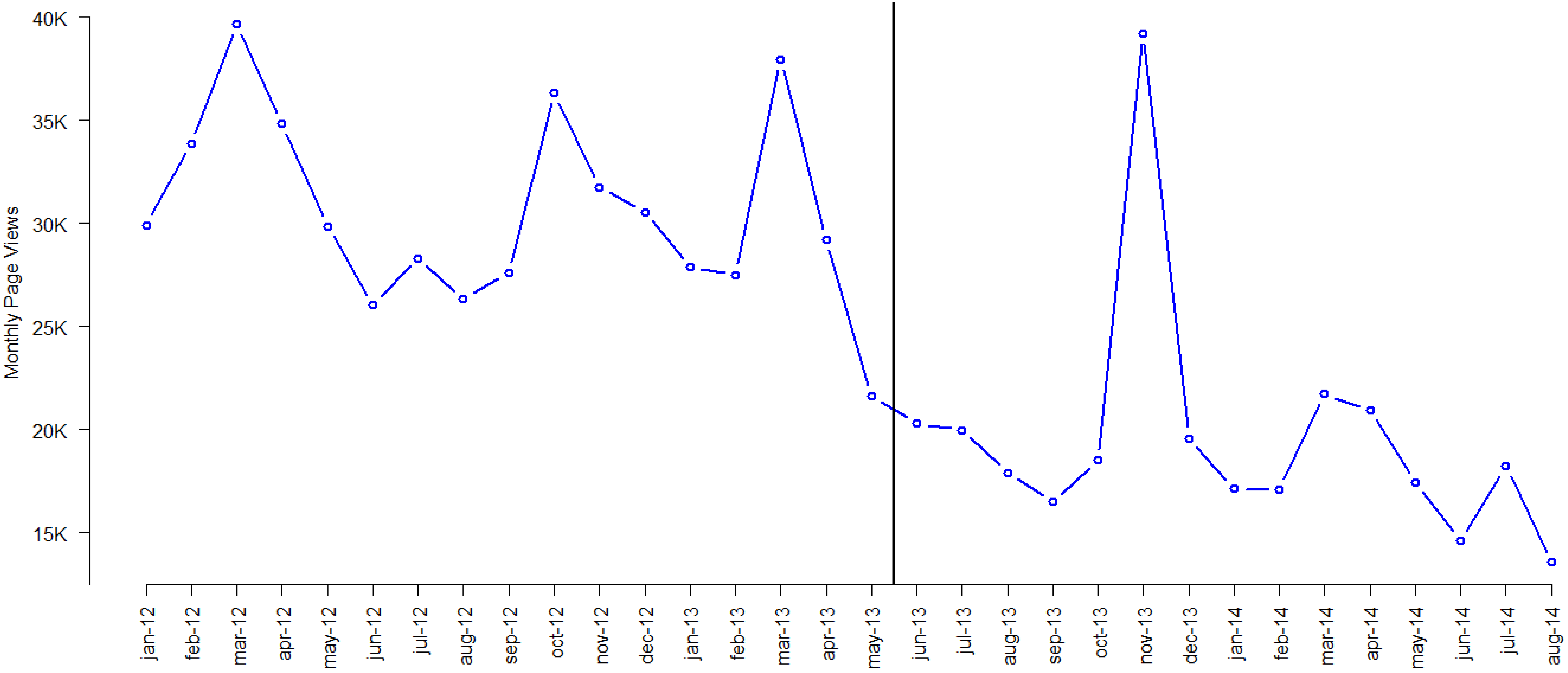
# Security: Page Views for secure_border_initiative



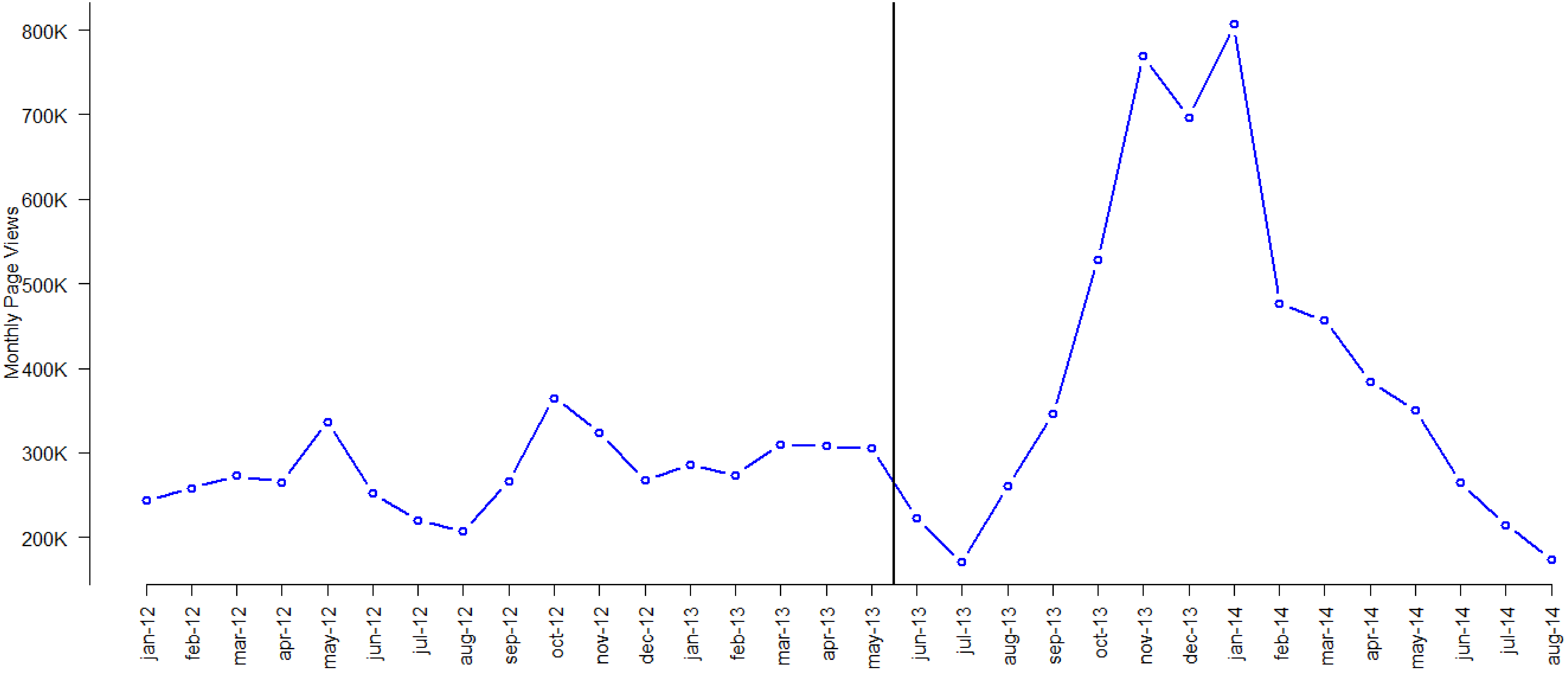
# Security: Page Views for Task_Force_88_antiterrorist_unit



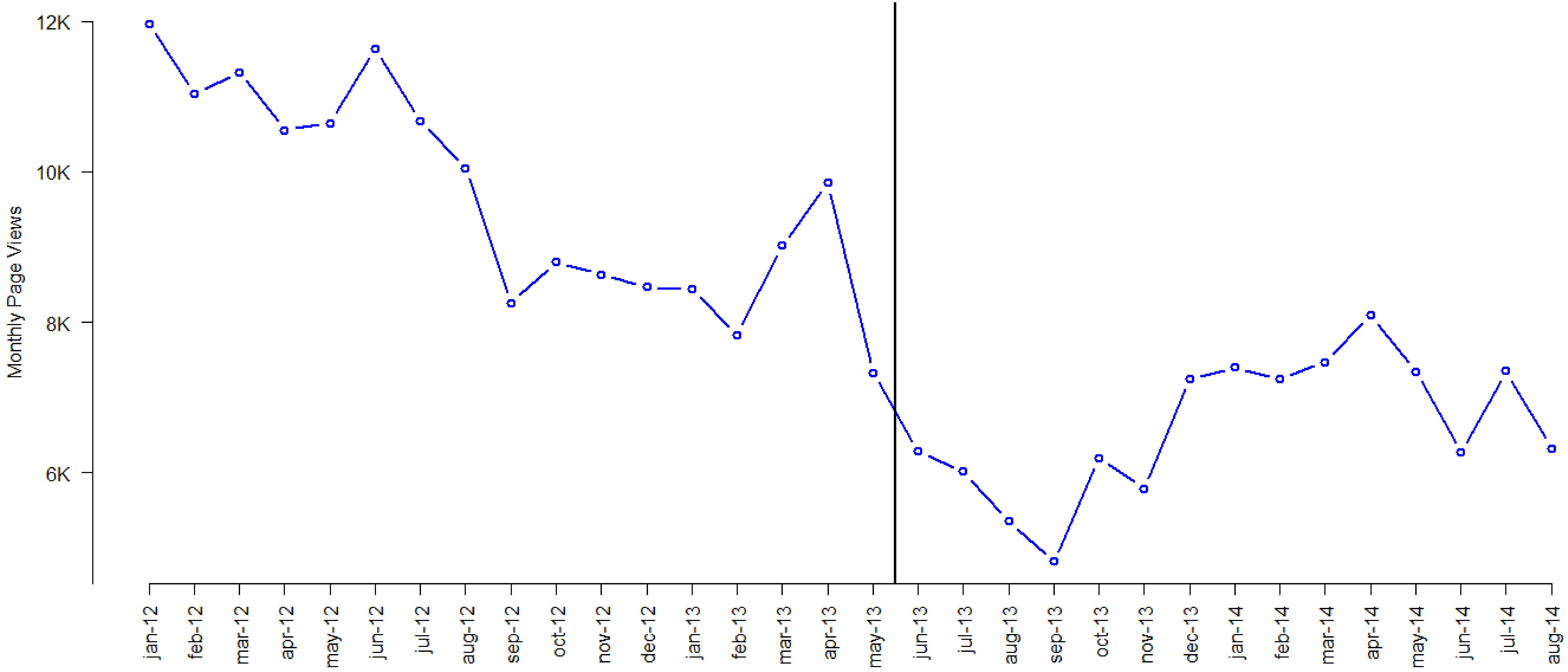
Security: Page Views for transportation_security_administ



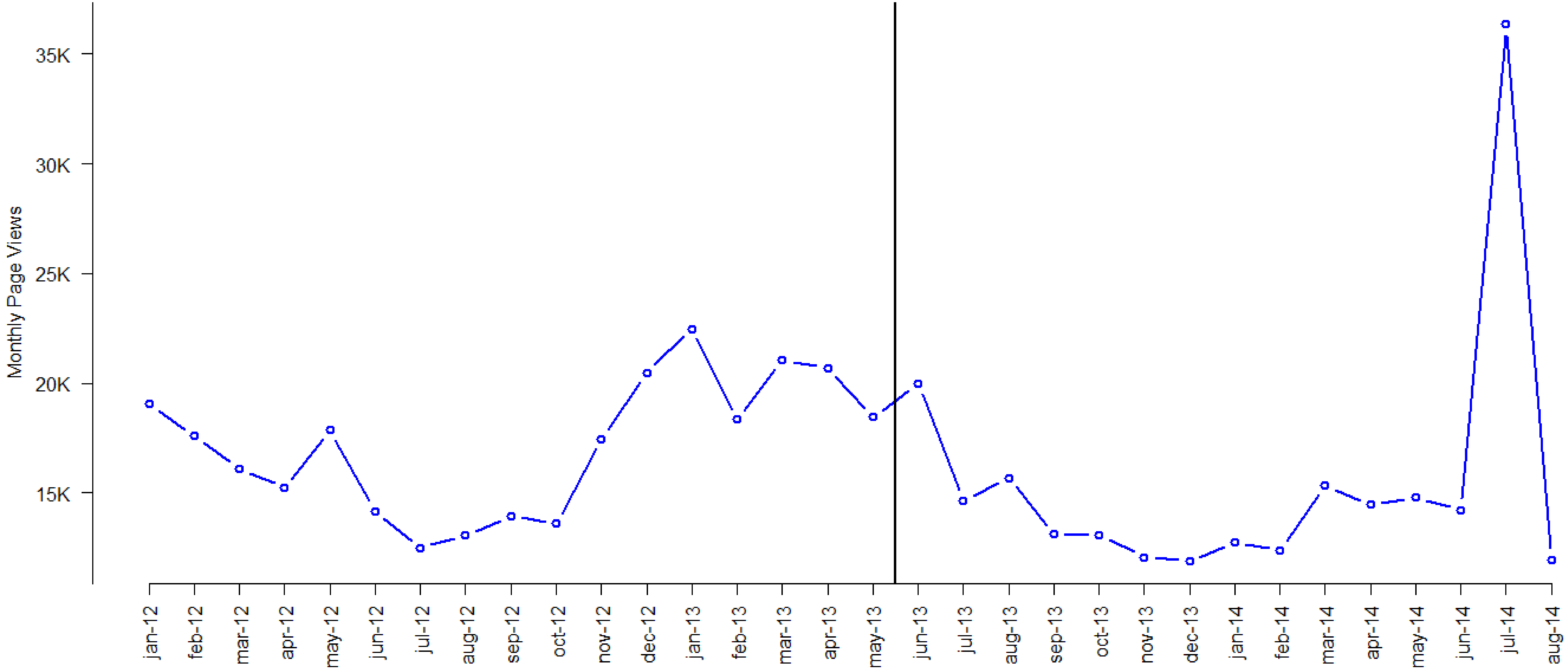
# Security: Page Views for united_nations



## Security: Page Views for us_citizenship_and_immigration_s

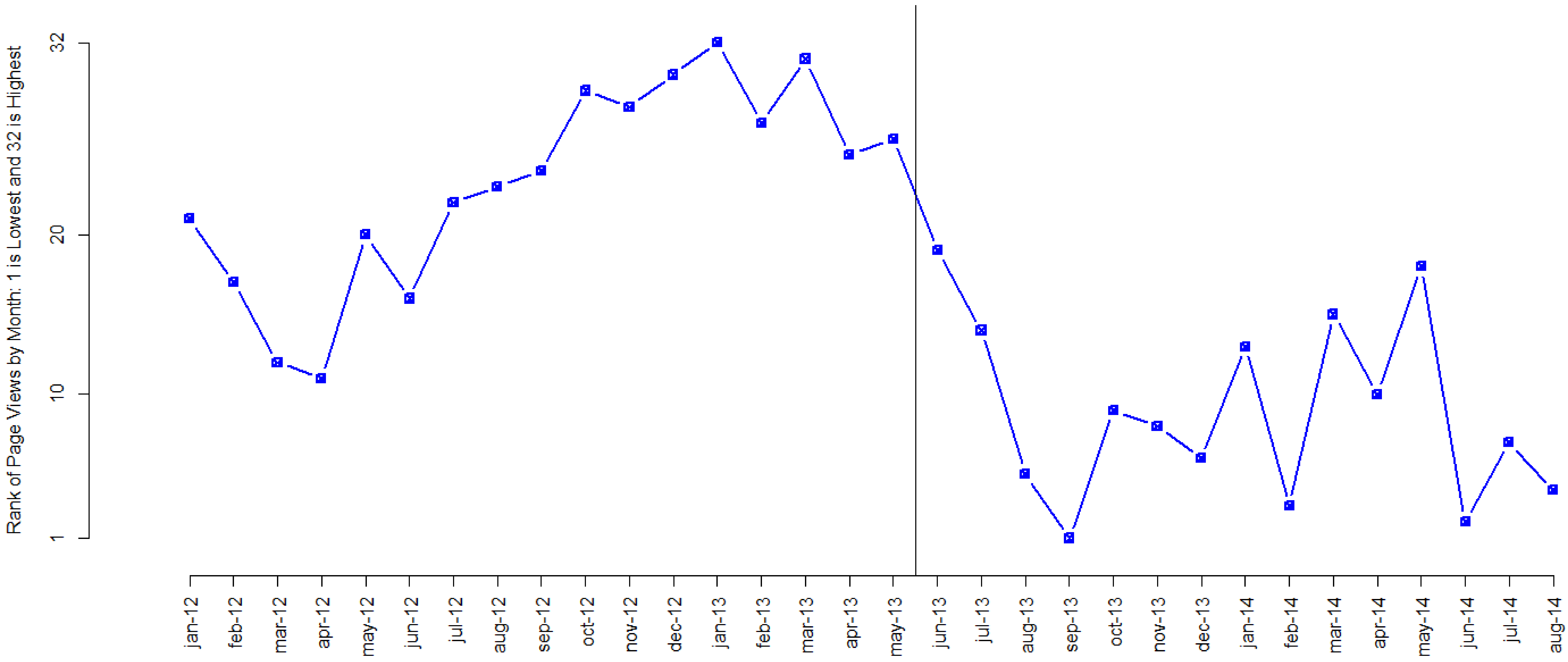


# Security: Page Views for us_immigration_and_customs_enfor

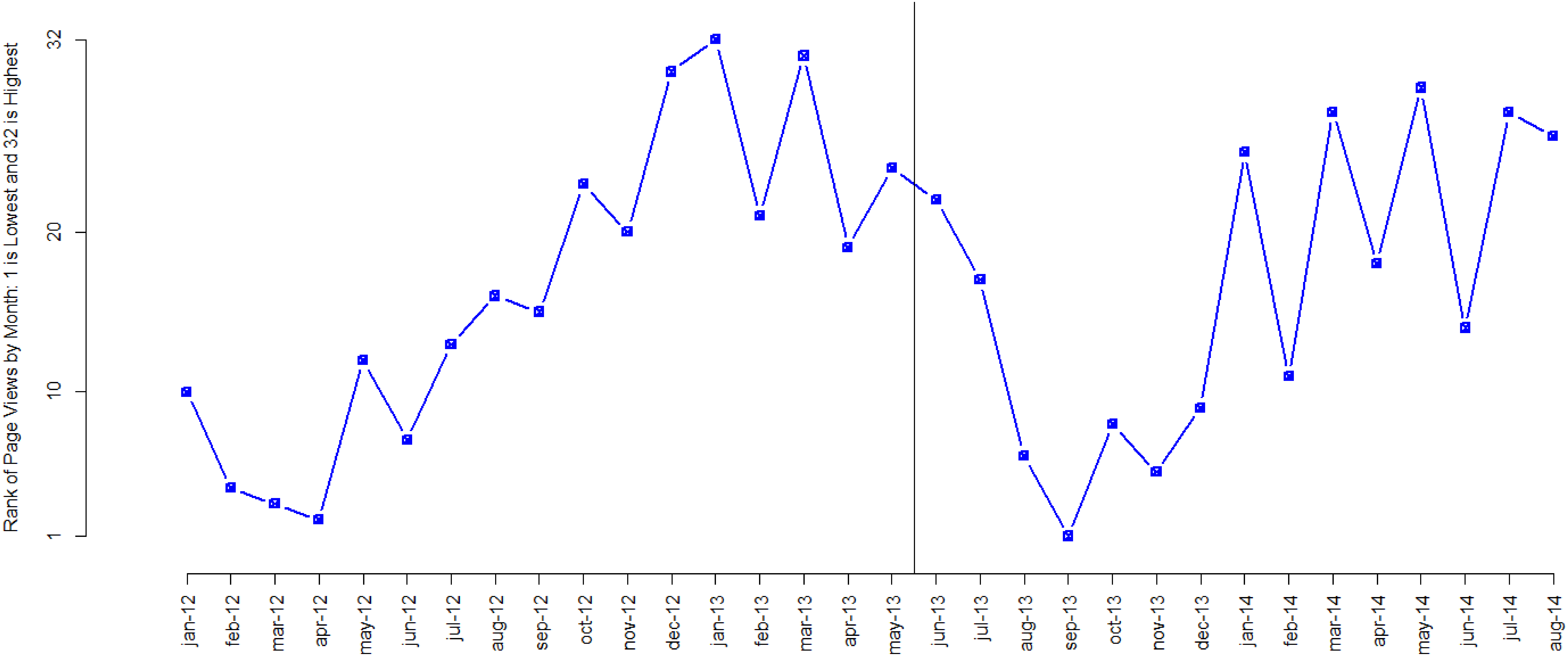


# APPENDIX VII: Page Views for Five Aggregate Comparison Datasets

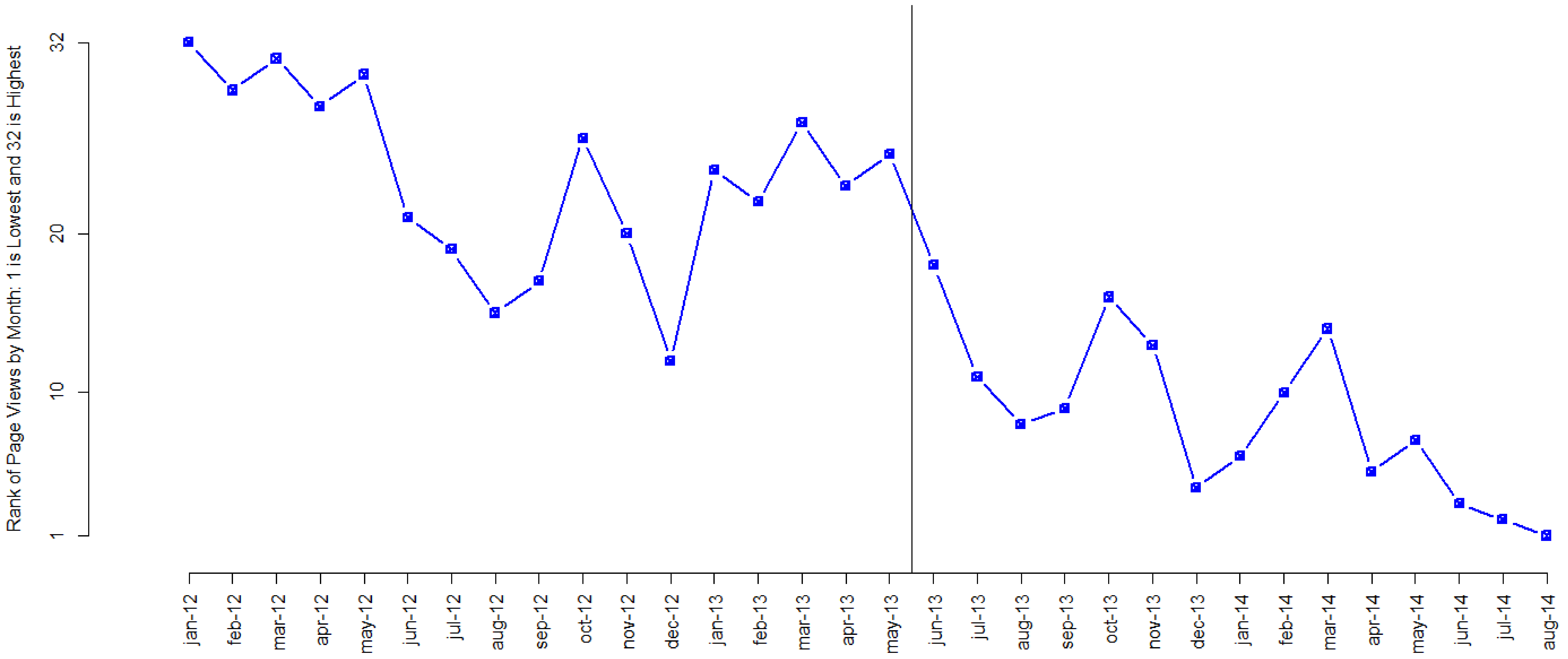
## Rank of Views by Month for Control: Global1



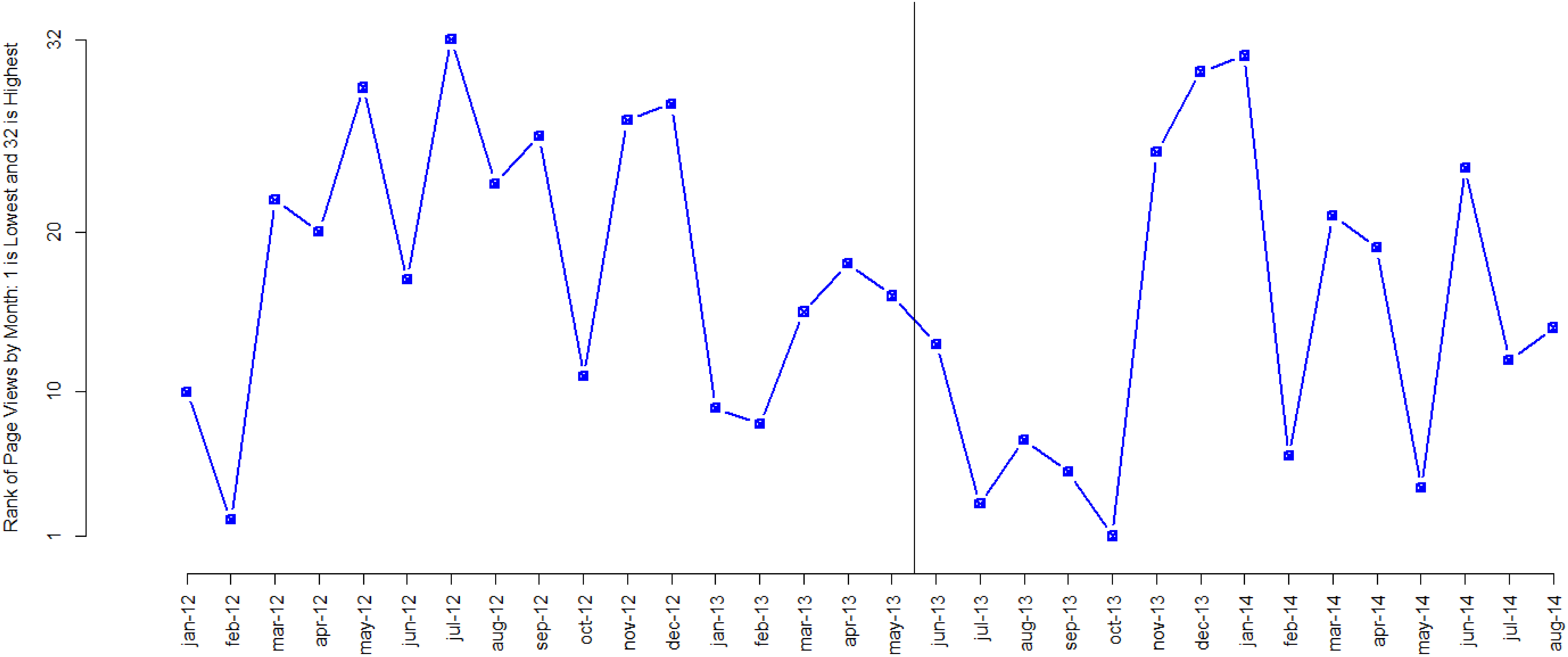
# Rank of Views by Month for Control: Global2



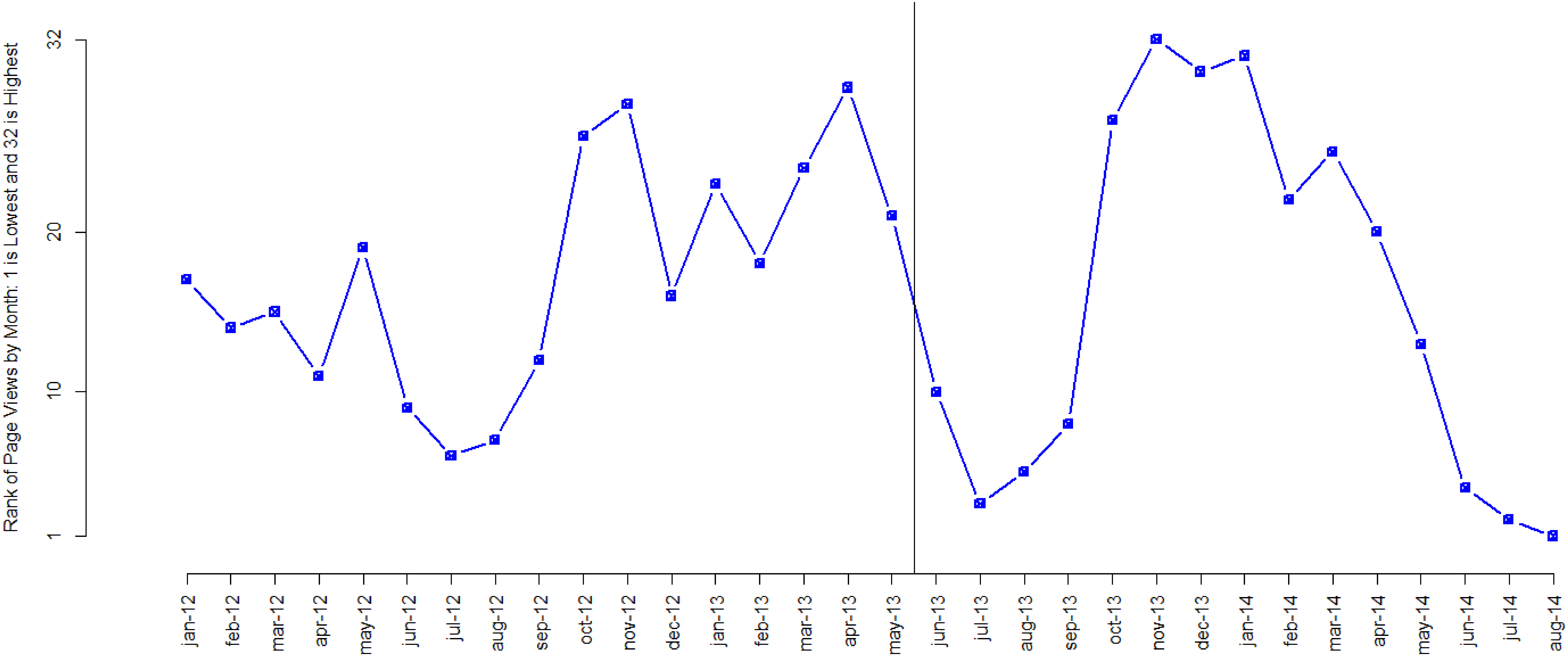
# Rank of Views by Month for Control: Infrastructure



# Rank of Views by Month for Control: Popular



# Rank of Views by Month for Control: Security



**IN THE UNITED STATES DISTRICT COURT**
**FOR THE DISTRICT OF MARYLAND**

| | | |
|---|---|---|
| WIKIMEDIA FOUNDATION,<br>Plaintiff,<br>v.<br>NATIONAL SECURITY AGENCY, *et al.*,<br>Defendants. | ) | Civil Action No. 1:15-cv-00662-TSE |

# Exhibit 17

# SECOND DECLARATION OF DR. ALAN J. SALZBERG

Dr. Alan Salzberg, for his second declaration pursuant to 28 U.S.C. § 1746, deposes and says as follows:

## I. Introduction

1. I am the Principal (and owner) of Salt Hill Statistical Consulting. I previously submitted a declaration in this case, dated February 14, 2019 ("Salzberg February Declaration"). My February declaration commented on the "Declaration of Jonathon Penney" ("Penney December Declaration"), which was submitted in December 2018. I submit this second declaration at the request of the United States Department of Justice in response to the "Reply Declaration of Jonathon Penney" ("Penney Reply"), which was submitted on March 8, 2019. I have previously submitted my resume describing my background and qualifications in statistical sampling, analysis, and review for government and industry, as well as information regarding prior testimony and fees.
2. This report proceeds as follows. In the next section, I summarize my findings. In the third section, I detail those findings. In the fourth section, I set forth my conclusions. Finally, I have included an appendix with a program log showing the results of additional analyses.

## II. Summary of Findings

3. In my February Declaration I addressed the deeply flawed model presented by Dr. Jonathon Penney in his December Declaration. Specifically, in summary I previously found as follows:[1]

   A. "The methodology used in the Penney Declaration—which purportedly shows an upward trend in page views of certain articles posted on Wikipedia through May 2013, followed by an abrupt drop and downward trend in views of those articles beginning in June 2013—is deeply flawed, inappropriate, and likely biased."

   B. "The Penney Model simply assumes that a single change occurred in June 2013, rather than letting the data identify the timing and number of changes in trends that occurred. Even though there is no consistent trend in the data, the design of the Penney Model will create the appearance that the data contain just one inflection point. And, because of its design—even though changes in trend occurred before these June 2013 disclosures—the Penney Model will find that the disclosures caused them."

   C. "Contrary to the hypothesis presented in the Penney Declaration, analysis of page views for the 48 individual articles in the privacy-sensitive group do not show a rising trend followed by an immediate and sustained drop in June 2013."

   D. "With the one exception of removing the article on Hamas, the Penney Declaration does no analysis or adjustment for factors (such as world events) affecting these individual article page views. Instead, the Penney Declaration inappropriately aggregates the vastly different page view data for individual articles, with the result that these individual differences in page views are masked."

[1] Salzberg February Declaration, paragraph 4.

E. "Even at that aggregate level, I find that the hypothesized peak in page views of "privacy-sensitive" articles in May 2013 does not exist, and the hypothesized upward and then downward trends in views of privacy-sensitive articles before and after June 2013, respectively, do not exist."

F. "Extended data through 2018 regarding page views of the privacy-sensitive articles do not indicate a long-term decline in page views from pre-June 2013 levels."

G. "A proper control dataset would exhibit similar page view behavior prior to June 2013. The comparison datasets used in the Penney Declaration do not and are thus inappropriate controls."

H. "The Penney Declaration analysis ends in July 2014. No data are presented that shed any light on whether page views at the time the Amended Complaint was filed in 2015 (or thereafter) were affected by Upstream. In other words, even if the purported effect and trends were a correct conclusion for the data examined (and they are not), the Penney Declaration analysis does not and cannot show that the effect continued years after the study ended."

I. "Even if a chilling effect occurred in June 2013, there are no data analyzed in the Penney Declaration that show any effect was due specifically to "public awareness of" the specific NSA surveillance program challenged here (known as Upstream surveillance) rather than possible inaccuracies, if any, about the program reported in the press, disclosures about other NSA programs, disclosures about other surveillance programs (e.g., surveillance by Britain), or other, unrelated events of June 2013."

4. As discussed in detail below, the Penney Reply does not raise any valid critiques of my original findings, and the additional analyses in the Penney Reply do not bolster the flawed model presented in the Penney December Declaration. In addition, the Penney Reply does not propose a new model that corrects the flawed model presented in the Penny December Declaration, and the slight modifications attempted do not address any of the issues I raised. Therefore, my findings and conclusions set forth in my February declaration remain unchanged.

## III. <u>Details of Findings</u>

5. The Penney Reply begins with seven critiques of my analyses, in paragraphs 4 through 23 of the Penney Reply, and goes on to respond to my critiques in paragraphs 25-36. I reviewed all of the Penney Reply and in this declaration I organize my responses by topic, so as not to be repetitive. In particular, this section proceeds with the following six subsections:

A. Overview of the Incorrect Assumptions Made in the Penney Reply;

B. Spurious Statistical Conclusions from the Penney Model are Partly Due to Aggregation of the Article View Data;

C. The Penney Reply's Additional Analyses Fail to Address the Flaws in the Penney Model;

D. Data Beyond Time Period 2014 Show Article Views at About 2012 through 2014 Levels, Even When Earlier Data is Corrected for Mobile Views;;

E. Omitted Variable Bias of the Penney Model Cannot be Solved by Deleting Valid Data; and

F. The Penney Model's Failure to Isolate the Effect of Awareness of NSA's Upstream Program.

## A. Overview of the Incorrect Assumptions Made in the Penney Reply.

6. Before responding to the specific claims of the Penney Reply, I first address some false assumptions the Penney Reply made regarding my critiques.

7. First, while my review of the disaggregated data provides an important, simplified explanation of many of the flaws of the Penney Model, the flaws of that model remain whether that model is applied to the aggregated or the disaggregated data. I am not suggesting that the application of the deeply flawed Penney Model to each of the 48 articles, individually, would be appropriate, nor am I suggesting that there could never be theoretical circumstances where the data could be aggregated without presenting the deeply flawed and misleading results that the Penney Model presented here.

8. Second, my February report provided no wholesale critique of the so-called ITS "Interrupted Time Series" designs or of regression models in general. My critiques instead relate to the particular methods Dr. Penney employed and the underlying data used in the Penney December Declaration.

9. Third, as I pointed out a number of times in my February Report,[2] I do not present an alternate model of page views, but I do use a number of examples and perform analyses that demonstrate the flaws in the Penney Model. Statements in the Penney Reply regarding "alternatives" that I suggest are therefore misleading.

10. Fourth, while the Penney Reply is correct in that much of my analysis uses "visual inspection" as an aid to understanding the issues with the Penney Model, I also perform statistical tests and point out many specific flaws in the Penney December models. As with the issue of aggregation and disaggregation, I am not advocating one or the other, but rather, doing both. A simple visual review of the data using charts and graphs, such as I the one performed, has long been considered a fundamental component to developing correct statistical models.

## B. Spurious Statistical Conclusions from the Penney Model are Partly Due to Aggregation of the Article View Data

11. As I stated in my original declaration, a review of the disaggregated data leads to the conclusion that there is no May 2013 peak or steep drop beginning in June 2013, contrary to the Penney December Declaration's conclusion.[3] The aggregated data do not show a May 2013 peak either, but rather an April 2013 peak,[4] followed by declines beginning in May 2013. This means that both the disaggregated data and the aggregated data show that the drop in page views begins *before* the June 2013 disclosures.

[2] In my February Declaration, for example, in paragraphs 52 (note 31) and 53, I explicitly state that I am not proposing an alternative model.

[3] Salzberg February Declaration, paragraphs 11-17.

[4] As stated, while the Boston Marathon bombings are one possible reason for an April peak, such a simple model is far from adequate for many of the same reasons that the Penney Model is inadequate, but at least in the April peak model, the drop in page views comes after the purported cause and not before the purported cause.

12. The Penney Reply responds to this critique by erroneously claiming that my disaggregated review should be disregarded because aggregation is appropriate here. This somewhat misses the point, which is that neither the disaggregated data nor the aggregated data support Dr. Penney's conclusions. Nonetheless, I reviewed the literature that the Penney Reply cites in support of its claim. The literature cited does not support the Penney Reply's claim.[5] The articles cited are general articles on ITS designs rather than articles espousing aggregation.[6] Moreover, the four reasons cited in the Penney Reply paragraph four are not specific to aggregated data (they apply equally to disaggregated data).

13. In paragraph 26b, the Penney Reply acknowledges that there is "there is no single determinative method or factor to decide whether an aggregated or disaggregated analysis of data is appropriate." As I stated, by aggregating all the data prior to analysis, there is no possibility of correcting for any article-specific differences in the data or exploring whether there are important differences among article views that need to be accounted for in any model. This leads to a biased model and erroneous claims of statistical significance where, as here, such differences exist.[7] The idea of not reviewing and understanding the disaggregated data, and discarding information by inappropriately aggregating that data, is anathema to scientists, because such ignorance often leads to false conclusions. That review typically includes graphical analysis, because, as one statistician put it: "[g]raphics reveal data. Indeed graphics can be more precise and revealing than conventional statistical computations."[8]

14. The Penney Reply argues that that my use of simple graphs to provide a visual inspection of the disaggregated data should be disregarded, in part, because a "visual inspection of data . . . can often be misleading," a point he makes with a quotation of one of the great proponents of graphical analysis, Dr. Howard Wainer.[9] Dr. Wainer, however, is not saying that graphs should not be used; he is only saying to be careful that they are not used in a misleading manner.[10] Ironically, by ignoring the disaggregated data and aggregating dissimilar page views to tell a

[5] Specifically, in the footnotes for paragraphs 4-5, the Penney Reply identifies several sources that Dr. Penney claims supports his use of aggregation in this circumstance. The only citation that even appears to support aggregation, in this type of situation, is not from a paper or textbook but from a PowerPoint presentation by Emma Beard which appears to have been presented at a conference in London (*see* footnotes 3, 4, and 21 in the Penney Reply). I reviewed the PowerPoint presentation and it presents no reasoning or data to support the claims (nor is it obvious that the author even made such claims regarding a simple regression model like the one in the Penney December Declaration). Additionally, unlike a scholarly article, a PowerPoint presented at a conference is typically accompanied by an oral portion of the presentation that may provide additional context or present the point differently than the language on the printed slides). In short, none of the cited source materials in the Penney Reply alter my conclusion that in this instance the use of aggregated data is inappropriate and misleading.

[6] The Penney Reply in paragraph 26e, takes issue with my terming the data "panel data" and not "time series" data. Panel data is a form of time series data, as the introduction to the text and chapter on panel data in my source make clear. See Wooldridge, Jeffrey M., <u>Introductory Econometrics, A Modern Approach, 5th Edition,</u> 2012, South-Western Cengage Learning, p. 10 and 448.

[7] See Salzberg February Report, paragraphs 56-60, for example.

[8] Tufte, Edward R., The Visual Display of Quantitative Information, Graphics Press LLC, 2001, p. 13. Also, p. 9 of the same text states that: "Often the most effective way to describe, explore, and summarize a set of numbers – even a very large set – is to look at pictures of those numbers. Furthermore, of all methods for analyzing and communicating statistical information, well-designed data graphics are usually the simplest and at the same time the most powerful."

[9] Penney Reply, paragraph 3 footnote 1.

[10] Quote from Penney Reply, paragraph 3 footnote 1 (quoting Howard Wainer).

misleading story, Dr. Penney has created precisely the type of misleading graphs that Dr. Wainer is warning against. As Yale statistician Edward Tufte says: "[a]ggregations by area can sometimes mask and even distort the true story of the data"[11] and "[a]ggregations over time may also mask relevant detail and generate misleading signals."[12] Tufte concludes:"[i]f in doubt, graph the detailed underlying data to assess the effects of aggregation."[13] As I explained in my first Declaration (Paragraphs 18-26), Figure 2 of the Penney December Declaration is misleading because it inappropriately aggregates the data and shows a suggestive regression line, while obscuring the fact that the decline was not as indicated.[14]

15. I created and included (as Appendix IV to my first Declaration) graphs of each of the 48 articles' page views individually, so that all the data is available to view in a clear graphical form. I invited (and invite) review of each of those graphs. The only reasonable conclusion from a review of those graphs is that the effect supposedly found in the Penney December Declaration is spurious. I also included graphs of the aggregated data (*see* paragraphs 18-26 of my February Declaration), and those graphs also do not indicate a May 2013 peak. I did not leave out anything or "cherry-pick," contrary to what the Penney Reply states in paragraphs 11, 12, and 32(a).[15]

16. The Penney Reply claims that disaggregation adds "noise" to the data, "both visual and statistical," and points to my first graph showing all 48 articles in a single figure.[16] I showed all the data in a single figure (as well as in 48 separate figures in Appendix IV) because it provides important context and a comparison point to Dr. Penney's aggregated plot, which artificially smooths the differences.[17] As a reminder, my Figure that includes all 48 articles is below.

[11] Tufte, Edward R., Visual Explanations, Graphics Press LLC, 1997, p. 35.

[12] Ibid, p. 36.

[13] Ibid, p. 37.

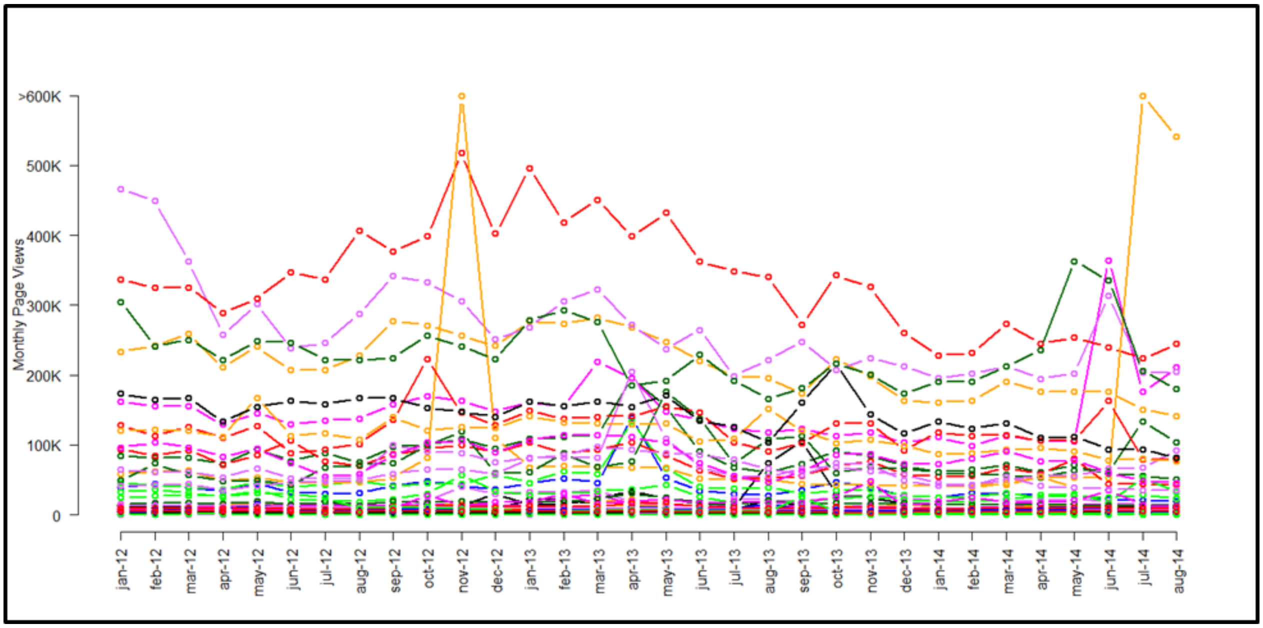
[14] Gelman, Andrew and Zelizer, Adam, "Evidence on the deleterious impact of sustained use of polynomial regression on causal inference," Research and Politics, January-March 2015, also cited in the Penney Reply, is also clear that graphical analysis is recommended.

[15] Penney Reply, paragraph 12.

[16] Penney Reply, paragraph 5.

[17] This method, of putting all the data into a single plot, is done in so-called spark graphs, examples of which can be found in Tufte, Edward R., Beautiful Evidence, Graphics Press LLC, 2006. p. 47-63.

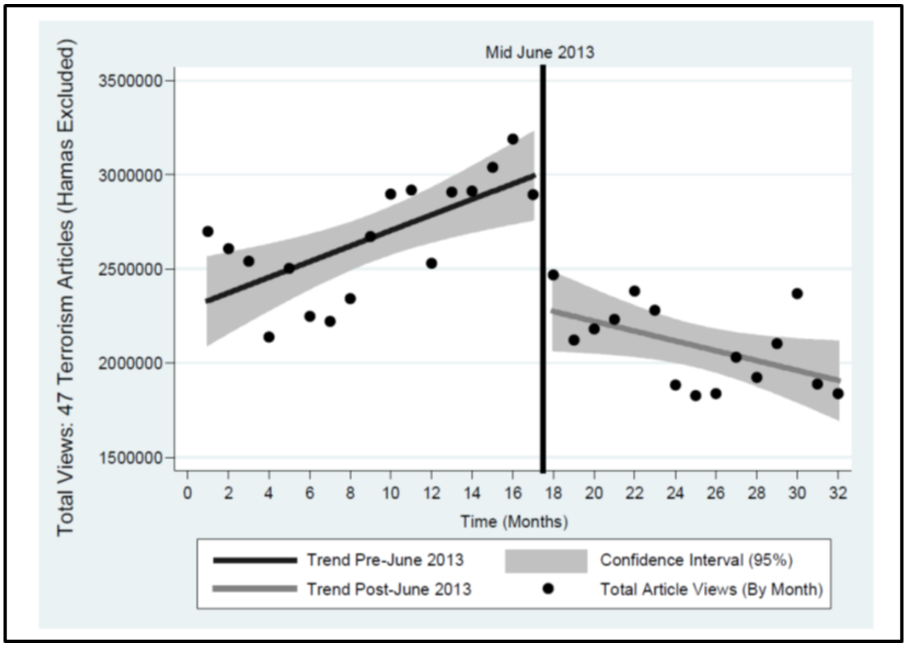
***Figure 1: Page Views for all 48 Articles Considered to Suffer from a Chilling Effect beginning in June 2013***



17. In contrast, Penney's Figure 2 from his December Declaration, shown below, misleadingly indicates a simple up and down movement that is belied by the individual data in Figure 1, above. The same is true for the confidence intervals drawn on Penney's Figure 2 graph itself, as I pointed out in my February declaration.[18]

[18] See Salzberg February Declaration, paragraph 20.

***Figure 2: Penney December Declaration Aggregate Figure Masks Individual Differences***



18. The contrast between the simple, disaggregated view and Penney's misleading aggregate view should have led Dr. Penney to question whether his aggregated model masks systematic differences at the article-level. As I stated above, I also provided each plot individually, so the reader can see what is behind the total picture of page-views shown in my first figure.

19. The Penney Reply is also wrong when it categorically states that disaggregation adds noise. The Penney Reply concerns that a disaggregated model will not allow for estimation of an "aggregate level inference about large scale NSA surveillance effects"[19] are misplaced. If the same naive model is run on both datasets, the estimated effect in the disaggregated model is exactly the same as the estimated effect in the aggregate model.[20] The statistical significance of these effects will also be the same if the disaggregation only adds noise to the model, and I show this fact through a simulation.[21]

20. However, if the disaggregated data reveal systematic differences in the data, in that the individual articles' page views do not tell the same or even a similar story as the aggregated data, then the naive model needs to be modified in order to avoid bias, whether run on aggregate or individual article data. To further support the analysis I already performed showing the model is over-simplified and perhaps mis-specified, I performed a statistical test to determine whether the

[19] Penney Reply, paragraph 26b suggests that because the question regards aggregate differences the aggregated data must be used.

[20] This fact is shown in the Appendix to this Declaration, and can be observed by noting the coefficient estimates for the Penney Model as shown in my Appendix. In the Appendix, I run the Penney Model on the averages and run the same model on the individual articles. The estimated effects (model coefficients) are exactly the same.

[21] I have included in the Appendix a simulation that shows the results of running the Penney Model on aggregated and disaggregated data are the same when the errors are statistical noise. This includes not only the regression coefficients (which will be the same whether the difference are due to noise or not, as explained above) but also the standard errors (i.e., the statistical significance) of those coefficients.

differences by article are mere noise or systematic.[22] I found, with high statistical significance, that the differences among articles are systematic (the statistical results are in the Appendix to this Declaration). This means that the model used in the Penney Reply is incorrect, *whether using the aggregated or the disaggregated data.* Only by accounting for the article-level, seasonal, and other differences can a valid model or set of models be produced. Furthermore, the model's estimates show increased error when calculated in disaggregated form.[23] This fact confirms my conclusions in my February report.[24] Because the differences are systematic and not mere "noise," the aggregation produces a result with inflated statistical significance.[25]

21. In reviewing some of the specific examples I cited to explain the fact that aggregating the data masks differences in the articles, the Penney Reply re-explains some analyses and runs additional models, but none address the issues I raised.[26] The Penney Reply presents Figures 2A and 2B, which purported show an "Increase until June 2013 and then a Sharp Drop-off."[27] This labeling is wrong. The increase is only through April, with a drop off in May and a continuation of that drop in June. This fact can be seen in Penney Reply's own Figures 2A, 2B, 3A, and 4 of the Penney Reply. Each shows an April and not a May peak, and a May and not a June start to the drop in page views. As I explain in my first Declaration, the fact that the drop in page views began *before* the June 2013 disclosures does not support Dr. Penney's conclusion that the June 2013 disclosures caused the drop in page views, and violates a basic tenet of causal models (i.e., a cause cannot occur after an effect).[28]

22. The models using the data in Figures 2, 3, and 4 of the Penney Reply suffer from the same problems as the original model in the Penney December Declaration.[29] The Penney Reply

[22] See Salzberg February Report, paragraphs 55-60 for my comments regarding the over-simplified model and omitted variable bias.

[23] As shown in my appendix, attached here, in some cases the claimed effects are not statistically significant. In other cases the statistical significance is weaker. These are further indications that the article differences are not mere noise. As my simulation (in the Appendix attached here) shows, when differences are based on mere noise, the statistical significance of the coefficients for the effects will remain unchanged when running the model on aggregated versus disaggregated data.

[24] See Salzberg February Report, paragraph 48-50 and 55-60.

[25] This is due to omitted variable bias, among other factors. I pointed this out in my February Report, paragraph 56. I do not attempt to correct for the omitted variable bias by adding additional variables, and therefore the disaggregated model is also incorrect.

[26] These re-analyses and the Penney Reply's commentary on them is found in Penney Reply, paragraphs 6-22 and paragraphs 26, 28, and 30.

[27] Penney Reply, Figures 2A and 2B.

[28] For two examples of such spurious inferences that ascribed a later cause to an earlier effect, see a source cited in the Penney Reply: McCleary, Richard, McDowall, David, and Bartos, Bradley J., Design and Analysis of Time Series Experiments, Oxford University Press, 2017. The examples are portrayed in this text in Figure 5.15 (explained on p. 214-215) and Figure 7.1 (explained on p. 275-276), and involve "interventions" and data with similarities to the data analyzed in the Penney December Declaration.

[29] The Penney Reply inexplicably discards its high-privacy group of 31 articles in favor of a new high privacy group of 23 articles for Figure 4 and some accompanying analyses. The Penney December Declaration already determined (perhaps also arbitrarily) a 31-article set that is highly privacy sensitive and this new set of 23 is a subset of those articles. Of course, re-running the same model on datasets that are nearly the same will produce results that are nearly the same, and proves nothing.

analysis ignores the large and obvious effect of events of April 2013 in its analysis of "improvised explosive device," "dirty bomb," "car bomb," and "ammonium nitrate."[30]

23. The only graph that the Penney Reply shows that appears to have a peak in May is Figure 3b (page views for so-called "normalized" Ammonium Nitrate), but that supposed "peak" is artificially created because the Penney Reply manipulated the graph to remove the April peak and replace it with the average of the March and May.[31] Removing such outliers and replacing them with averages in this way is against the practice of statisticians in general. Outlier handling is discussed in detail in an article the Penney Reply cites (at footnote 8), and this article says such adjustment is only appropriate for *error* outliers.[32] Here, the data points for Ammonium Nitrate page views are not errors and so removing the correct data point and replacing it with an average is inappropriate.[33]

## C. The Penney Reply's Additional Analyses Fail to Address the Flaws in the Penney Model

24. Paragraphs 18 and 28 of the Penney Reply assert that no assumption is made in the Penney Model concerning a May peak. However, the Penney Model hypothesis is a single trend line through May 2013, and then a second line, starting in a potentially different place. The assumption is a single point of inflection, and that point is a peak in May and a drop off beginning in June.[34] While it is correct that the model can find that there is no peak at all in the data, my point is that no other month is modeled as a possibility, and that if the data goes up and down, the model finding a June peak will be statistically significant even though the peak did not occur in May and the drop did not begin in June.

25. The Penney Reply in paragraph 28 criticizes my demonstration, using a polynomial model, that the peak did not occur in May and says such an approach is biased, citing a scholarly article.[35] That article refers to higher order polynomials (which I did not use) and, even for higher order polynomials, the article does not say that such models are biased, only that they may not reduce bias.[36] Indeed, as shown in the quote below, the article brings up the same issues that I do with

[30] While the Boston Marathon bombings did not use ammonium nitrate and were not a "dirty bomb," this does not mean they may not have been a reason for a huge uptick in page views. Some news articles (for example https://www.theatlantic.com/technology/archive/2013/04/new-boston-bomb-parts-photos/316183/ ) discussed the possibility of ammonium nitrate being used. Even if the Boston Marathon bombings had nothing to do with the April uptick in page views, the complete exclusion of any cause of those changes biases the Penney Model, as I have explained.

[31] Penney Reply, paragraph 14 and footnote 8. See page 11 of the Penney Reply for the graph of Ammonium Nitrate views without April data deleted and replaced with the average of March and May 2013.

[32] The article is Aguinis, Herman, Gottfredson, Ryan K., and Joo, Harry, "Best-Practice Recommendations for Defining, Identifying, and Handling Outliers," Organizational Research Methods, 16(2), 2013, p. 270-301.

[33] Neither Dr. Penney nor I have suggested that the change in views in ammonium nitrate in April 2013 was due to an error in the archives used to collect the data.

[34] Penney December Declaration, paragraph 23, describes the design as testing for a "decrease in level and trend" beginning in June 2013.

[35] The article, cited in paragraph 28(b), footnote 32 of the Penney Reply, is Gelman, Andrew and Zelizer, Adam, "Evidence on the deleterious impact of sustained use of polynomial regression on causal inference," Research and Politics, January-March 2015

[36] Gelman, Andrew and Zelizer, Adam, "Evidence on the deleterious impact of sustained use of polynomial regression on causal inference," Research and Politics, January-March 2015, p. 5.

respect to simplistic linear models, saying that modeling higher polynomial effects does not necessarily fix those issues:

> "the higher-order polynomial has the effect of slightly modifying and improving the fit of the natural linear model. In criticizing the use of high-degree polynomials in RD [RD stands for Regression Discontinuity—the issue theorized in the Penney December Declaration] adjustments, we are not recommending global linear adjustments as an alternative...We recommend that any RD analysis include a plot such as Figure 1 showing data and the fitted model, and that users be wary of any resulting inferences based on fits that don't make substantive sense."[37]

26. In other words, plotting the data is recommended, and the authors are not recommending that a simple linear model is better than a polynomial one. Indeed, they preface that discussion specifically with:

> "Our point here is not to argue that the linear model is correct...Our point is rather that the headline claim, and its statistical significance, is highly dependent on a model choice that may have a data-analytic purpose, but which has no particular scientific basis. Figure 1 indicates to us that neither the linear nor the cubic nor any other polynomial model is appropriate here. Instead, there are other variables not included in the model which distinguish the circles in the graph."[38]

27. I include these extended quotes because despite the Penney Reply's misinterpretation, the article is useful in that it points out the very issue of spurious statistical significance and omitted variable bias that is at the heart of my critiques of the Penney Model in the first place.

28. Next, Paragraphs 19 through 22 of the Penney Reply describes a series of analyses of the single peak May model against other single peak models, concluding that the June model (with a May peak) is better than the others. These analyses are flawed in numerous ways.

29. First and most importantly, the entire exercise is based on a mischaracterization of my critique that implicitly assumes I am proposing a model with an April peak. I merely stated that a *naive* model such as the Penney Model could also be used to "prove" an April peak, meaning that such an analysis could also lead to spurious statistical significance. None of the Penney Reply analyses question this fact. I am not proposing that the data experienced a single change that caused the trend to abruptly reverse after April 2013 (a peak in that month and a decline thereafter). As I have stated numerous times, the data do not indicate a single change model is appropriate, whether that single change is in June 2013 or in some other month.

30. Second, in paragraph 19 of the Penney Reply, Dr. Penney attempts to complete a cross-validation analysis that uses three data sets for each of these article sets. However, two of the three models proposed in paragraph 19 of the Penney Reply, the "total page view" model and the "average total page view" model, are exactly the same statistically.[39] The total page view is simply the average page views multiplied by the number of articles. These two models are equivalent,

[37] Ibid, p. 6.

[38] Ibid, p. 3-4.

[39] Penney Reply, paragraph 19.

statistically, since regression models are invariant to changes in units.[40] For example, suppose we were trying to predict how far a person can jump according to their height in feet, and we ran a regression model that predicted someone who is 6 feet tall can jump 10 feet on average. If we use the same data but run the regression model based on inches, that new model would predict that someone who is 72 inches tall can jump 120 inches on average – in other words, the prediction is unchanged except for the expression in inches instead of feet.

31. The same is the case with running one model on the total and a second on the average, as is done in the Penney Reply (the results of which are summarized in the Penney Reply, paragraph 22). The model is unchanged but one is in terms of averages and one is in terms of totals. Therefore, the estimates for the model run on totals will be 23 times the estimates for the model run on the averages (for the Penney Reply model that has 23 articles). Thus, for example, in the Appendix to the Penney Reply showing the "23 Most Privacy Sensitive Article Set Cross Validation Analysis" (page 41), the coefficient for the variable *time* for the total model is shown to be 21,383.58. Two pages later (page 43), the same coefficient for the variable *time* in the average model is 929.72, which is exactly 21,383.58 divided by 23. The summary statistics like the t-statistic, which is 5.30, are also exactly the same.[41] The Root Mean Square Error and Mean Absolute Errors highlighted for the total model are 89,506.35 and 63,503.27 (on page 41), which, when divided by the 23 articles considered, is equal to the highlighted totals of 3,891.54 and 2760.94 shown for the average model for the highlighted RMSE and Mean Absolute Error, respectively, shown in the attachments to the Penney Reply (on page 43).[42]

32. Thus, while the Penney Reply asserts that there are 48 models (3 models by 4 datasets by 4 change points), there are really only 32 (2 models by 4 datasets by 4 change points). The four datasets also largely overlap, since the 46 article dataset includes all 44 articles in the 44 article dataset, which includes all 23 articles in the 23 article dataset, which includes all 21 articles in the 21 article dataset. In addition, the four months modeled are adjacent, meaning the regression models are very similar (this was part of my original point that the specification of the change point does not make much difference). In other words, though the Penney Reply asserts there are 48 separate models, there are only 32, and most of the 32 are highly related to one another and must produce similar results.

33. Third, the Penney Reply's use of cross validation is misplaced and performed incorrectly. In part the Penney Reply employs a "cross validation analysis."[43] This approach, which the Penney Reply uses to delete different time periods one at a time, is improper for time series models, in which the data points are related to one another.[44] In addition, the Penney Reply's cross

[40] See, for example, Wooldridge, Jeffrey M., Introductory Econometrics, A Modern Approach, 5th Edition, 2012, South-Western Cengage Learning, p. 40-41.

[41] The r-squared and the p-values are also exactly the same.

[42] There is a slight difference due to rounding or less than 1 for each of the figures.

[43] Penney Reply, paragraph 19.

[44] This is because the data in the cross validation set, or the data "left out", is not independent of the other data. See for example, Bergmeir, Christopher, and Benitez, Jose M., *"On the use of cross-validation for time series predictor evaluation,"* Information Sciences, 2012, 192-213. This paper discusses some of the fundamental problems with traditional cross-validation in time series, primarily in Sections 3.3 and 3.4. Also, see David R. Roberts, Volker Bahn, Simone Ciuti, Mark S. Boyce, Jane Elith, Gurutzeta Guillera-Arroita, Severin Hauenstein, José J. Lahoz-Monfort, Boris Schröder, Wilfried Thuiller, David I. Warton, Brendan A. Wintle, Florian Hartig and Carsten F. Dormann, *"Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure," Ecography 40: 913-929 (913-925 in particular), 2017.*

validation's purpose is to compare the June model to models with a different change point. None of the Penney Reply's cross validation analyses compare the simple single-change model to a model that accounts for other factors or otherwise corrects for omitted variables. Therefore, the Penney Reply's use of cross-validation to compare models and the attempt to show a May Peak model is better than an April peak model or other models are mere distractions that are not related to my criticism.

## D. Data Beyond 2014 Show Article Views at About 2012 through 2014 Levels, Even When Earlier Data is Corrected for Mobile Views

34. In my February Declaration I pointed out that the extended view of page view data also does not indicate any long term decline. The Penney Reply, in paragraphs 23 and 34(g), responds to point out that my extended data includes mobile use while the original data presented in the Penney December Declaration did not. To address this "apples to oranges" comparison, I therefore adjusted the 2012 to 2014 data to account for mobile usage. As I describe below, this adjustment has no effect on my conclusions.

35. I also considered the effect that the non-inclusion of mobile usage and the lack of adjustment of that increasing usage had on the Penney Model. I find that such exclusion and lack of adjustment are additional flaws in the Penney Model. Specifically, the Penney December Declaration data excluded mobile page views from the terror and control data sets.[45] If these views were a constant percentage of total views, such an exclusion would likely not affect the Penney Model. However, as I explain below, there was a dramatic increase in mobile web access from January 2012, the first month of data included in the Penney December Declaration analysis, to August 2014, the last month included.

36. The data provided with the Penney December Declaration (but not used in the Penney December Declaration or the Penney Reply) indicates that in January 2012, mobile views accounted for about 12% of total page views.[46] By the end of the study period, that figure was 32%. In other words, the Penney December Declaration's exclusion of mobile views had an increasingly downward bias on total page views. This is yet another bias that affects the Penney Model, and, by not accounting for mobile visits, the Penney Model is biased toward finding an effect and toward finding a larger effect. This bias is a result of the fact that for later data the model excluded more views than for earlier data.[47]

37. In terms of my graphs of extended data as compared to earlier data, the data prior to August 2014 would be higher with mobile data. My graphs included the data as originally provided with the Penney December Declaration, which did not include mobile data for the terror articles. Using

[45] It may be that mobile views were not available, in which case an adjustment, like the one I made, could have been made; or the Penney Model could have included a factor that accounts for such usage.

[46] This is based on the difference between the global English page views non-mobile and the total global English page views, and is consistent with this article https://techcrunch.com/2016/11/01/mobile-internet-use-passes-desktop-for-the-first-time-study-finds/.

[47] While it may seem that simply using desktop views only would not cause a bias to the results, this notion is not correct. To the extent that 1) mobile use was growing during the period, and 2) individuals were using mobile instead of (rather than in addition to) desktop views, the desktop views would be depressed in the latter part of the period and thus bias the results. This has occurred to such an extent that an increasing number of people rely exclusively on mobile access. See, for example, https://techcrunch.com/2016/11/01/mobile-internet-use-passes-desktop-for-the-first-time-study-finds/.

the Penney December Declaration's global article view dataset, which provides total views as well as total views excluding mobile, I adjusted the page views for the terror articles from January 2012 through August 2014 to account for mobile views.[48] The graphs below, showing the extended average and median page views with mobile page views factored in, are consistent with my earlier graphs of the extended data in that they indicate there was no downward trend after June 2013.[49]

38. Average and median page views appear to decline some in mid-2017 but views in 2015 and 2016 appear to be at or above 2012 through 2014 levels. It is also notable in these longer data series that there are clear peaks around the times of major U.S. or European terror attacks, adding further evidence that any reasonable model would account for such attacks (and of course the Boston Marathon bombings occurred very close to the time of the alleged drop due to the Snowden disclosures).

[48] This rough adjustment is undoubtably inaccurate but captures the magnitude and pattern of the mobile views.

[49] The adjustment results in an increase in article views for each month from January 2012 through August 2014, with the amount of increase depending on the share of total Wikipedia views that were mobile.

*Figure 3: Average Page Views, Adjusting Data Before 2015 to Factor in Mobile Page Views*

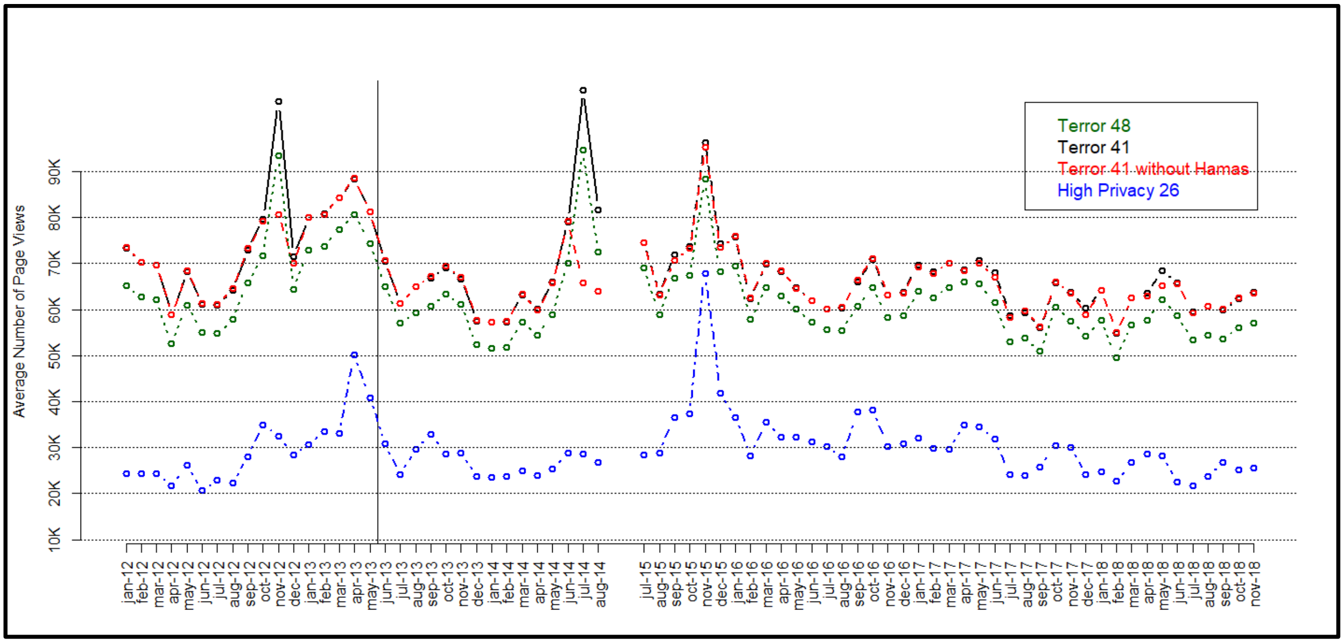
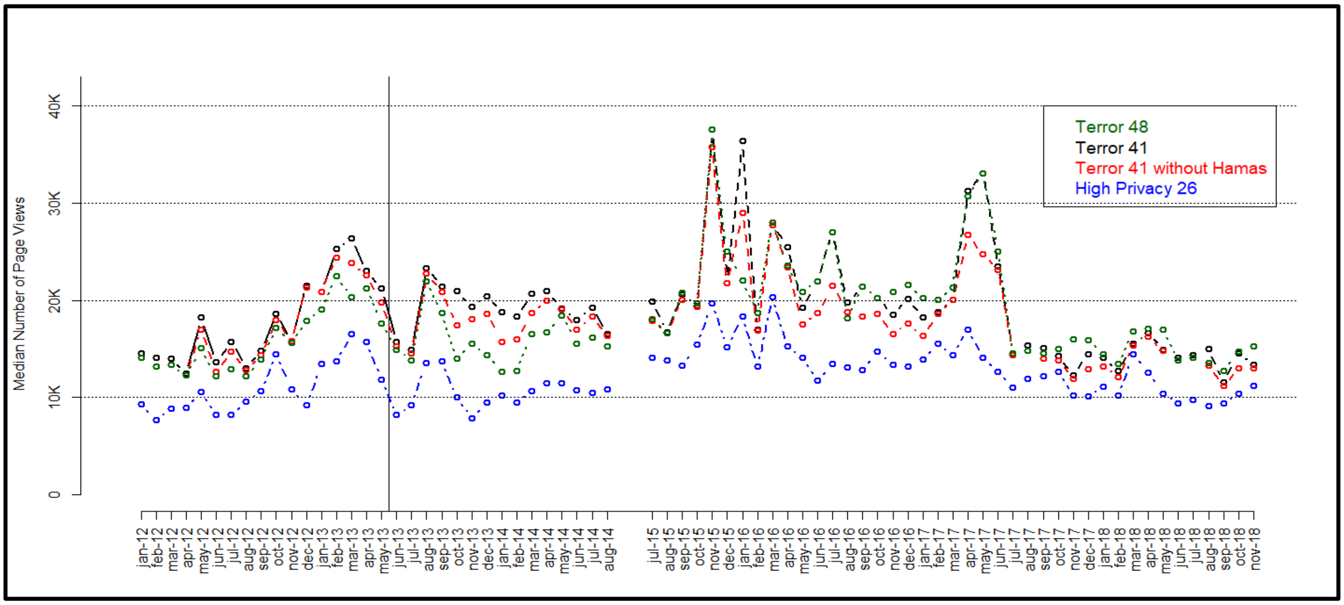


*Figure 4: Median Page Views, Adjusting Data Before 2015 to Factor in Mobile Page Views*



39. The Penney Reply cites some studies that purport to support the idea that the Penney December Declaration conclusions would continue beyond August 2014, but the Penney Reply neither considers (nor produced in this case) the data underlying those other studies. Even if those studies were to be based on a solid scientific and statistical grounds (and I cannot evaluate whether this is true without the underlying data), they only claim to offer conclusions applicable

to (at the latest) 2015.[50] Moreover, only one of the studies Dr. Penney cites in his reply appears to look at web data, rather than interview answers, and that study is from a working paper that was not published in a scientific journal and it expressly states it only includes data from 2013, and thus does not include any extended data. In any case, there is no way for me to evaluate the validity of those results, because I was not provided the data and it is not publicly available.

40. I do note that one article[51] cited in the Penney Reply footnote 44 adjusts for additional variables and appears to find a smaller (and not statistically significant) effect in terms of drops in searches. This finding is consistent with omitted variable bias I outlined in my first Declaration with respect to the Penney December Declaration.[52]

## E. Omitted Variable Bias of the Penney Model Cannot be Solved by Deleting Valid Data.

41. In my February declaration, I pointed out a number of omitted variables that cause bias to the estimates made in the Penney December Declaration. These variables include ones associated with seasonality, individual differences in articles, and news events (the Boston Marathon bombings in particular).[53] The Penney Reply leaves these largely unaddressed but does assert it controls for seasonality because it includes more than one year of data before and after June 2013.[54] However, despite having sufficient data (barely), the Penney Model makes no correction for seasonality and includes no analysis that shows there is not such an effect. I showed such seasonal changes appear in this data and they are statistically significant.[55] In other words, though there was sufficient data, and that data shows statistically significant seasonal effects, the Penney December Declaration ignored seasonality. Wikimedia acknowledged these effects during the deposition of its designee, James Alexander: "global user base, especially in English Wikipedia, tends to have a bit of a dip during the summer, just because there are people out of school, and a lot of people use it in school or when they are studying."[56] Curiously, the Penney Reply, paragraph 30a, states that there is "no basis to expect large seasonal effects with these page views." This statement is speculation that flies in the face of the qualitative and statistical evidence.

42. The Penney declaration correctly states that "in a naturalistic study outside the experimental context, it is not possible to control for all confounding factors."[57] However, the Penney December Declaration corrects for no confounding factors. As one recent author put it: "Obviously, one cannot include in a regression every variable that might conceivably be relevant. But when a factor has a reasonable chance of being important, to exclude it from the modeling is to risk substantial distortion."[58] The Penney Reply re-asserts that the comparator datasets help

[50] Penney Reply, paragraph 34.

[51] Section 3.2 of the article Marthews, Alex, and Tucker, Catherine, "Government Surveillance and Internet Search Behavior," February 17, 2017, found at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2412564 .

[52] See p. 38 in Marthews and Tucker for lack of statistical significance. For my discussion of omitted variable bias, see Salzberg February Declaration, paragraphs 55-60.

[53] Salzberg February Declaration, paragraphs 55-60.

[54] Penney Reply, paragraph 30a.

[55] Salzberg February Declaration, paragraph 57.

[56] Deposition of Wikimedia designee, James Alexander, April 12, 2018, p. 145.

[57] Penney Reply, paragraph 30e.

[58] Barnett, Arnold I., Applied Statistics: Models and Intuition, Dynamic Ideas LLC, 2015, p. 582.

control for confounding factors, but this is not correct for article-specific factors and is not true when the comparator data is not comparable, as I showed in my February Declaration.[59]

43. In some of the re-analyses in the Penney Reply, articles or time periods are deleted and the Penney Model is re-run.[60] It may be that the Penney Reply does this to address particular examples of the data not following the Penney Model. However, as I said above, these re-analyses do not support the results any more than the original analysis in the Penney December Declaration. Furthermore, by deleting data that tends to disprove the Penney Model and then re-running that data rigs the results toward adoption of the flawed Penney Model.

44. The Penney Reply seems to misinterpret my remarks concerning the staleness of a 2011 DHS list.[61] I was not commenting on the objective nature of the selection, but rather that any list gets stale over time, and the list here used is no exception. For that reason, the static list has no mechanism to update the key articles and therefore a natural decline occurs. The same was not true for the comparator list of popular articles. Because the determination of which articles were popular was made after the time period studied in the Penney December Declaration, articles such as Deaths in 2014 -- which had virtually no page views in 2012 -- were part of the list.[62] On the other hand, a group like ISIL/ISIS, which gained prominence in 2014, was not on the 2011 list, as I pointed out.[63]

## F. The Penney Model's Failure to Isolate the Effect of Public Awareness about the NSA Upstream Program

45. My sixth critique, discussed in my February declaration, is that "there are no data or statistical analysis offered that indicate such an effect [an abrupt decline in page views] was due to awareness of the specific NSA program at issue here rather than other related or unrelated events of June 2013."[64] The Penney Reply acknowledges that "in any study of naturalistic changes in human behavior, it will not be possible to isolate the source of all causes and effects on behavior" and that my critique is "a general observation about a *[sic]* naturalistic studies."[65] While this is correct, the Penney December Declaration analysis does not adjust for *any* of those causes, even the obvious ones like seasonality that affect summer page views.

46. Furthermore, the fact that the Penney Model may have been doomed from the start in terms of isolating the effect it intended to prove is not a reason for accepting the model; rather, it is a reason for rejecting it. Despite the passage of nearly six years since the Snowden disclosures, the Penney Reply does not cite a single study published in a peer-reviewed scientific journal that demonstrates the particular effect or even any chilling effect on Internet usage due to awareness of the actual operation of NSA programs.

[59] Salzberg February Declaration, paragraph 32-46.

[60] In Figure 3b and its explanation in the Penney Reply, the key month of April 2013 is deleted. In Figure 4 and accompanying analyses in the Penney Reply, eight of the original 31 high-privacy articles are deleted for reasons that are unclear to me and unstated in the Penney Reply.

[61] Penney Reply, paragraphs 31 and 32, refer to this critique.

[62] Salzberg Paragraph 64 and database showing 26 most popular articles, which accompanied the Penney December Declaration.

[63] Salzberg Declaration, paragraph 63.

[64] Salzberg Declaration, paragraph 66.

[65] Penney Reply paragraph 36a and 36c, for the first and second quoted material, respectively.

## IV. Conclusion

47. In conclusion, my original critiques, detailed in my February Declaration are unchanged by the Penney Reply. In short, the analysis in the Penney December Declaration and the Penney Reply fail to show that public awareness of the Snowden revelations regarding the NSA Upstream program caused any drop in page views of Wikipedia articles.

I declare of penalty of perjury that the foregoing is true and correct to the best of my knowledge and belief. Executed in New York, New York on March 22, 2019.

Alan J. Salzberg, Ph.D.
March 22, 2019

## Appendix: Stata Program Log

The following log shows the results of the analysis I performed and described in this declaration. The program was run using Stata, Version 14.

```
      name:  <unnamed>
       log:  
D:\clients_2018\DOJ_Wiki_NSA\programsdata\penneyreply\regression_effects_20190318.log
  log type:  text
 opened on:  19 Mar 2019, 11:01:40

. clear

. 
. insheet using orig48long.csv
(23 vars, 3,504 obs)

. drop if artnames=="Hamas"
(73 observations deleted)

. save orig48long, replace
file orig48long.dta saved

. keep if monthindex<=32
(1,927 observations deleted)

. save orig48long32, replace
file orig48long32.dta saved

. 
. *
. * Simulation that shows no difference in agg v. disagg if same model is run and
issue is just noise
. *
. use orig48long32, clear

. drop if artnames=="Hamas"
(0 observations deleted)

. drop if monthindex>32
(0 observations deleted)

. * run regression to get forecast error
. * no need to show output (but will show output of this for a different purpose
below)
. regress pageviews monthindex intervention postslope, noheader notable

. predict pviewmont
(option xb assumed; fitted values)

. predict sf, stdf

. * simulate data with same forecast error and run regression on disagg
. sort artnum monthindex

. isid artnum monthindex

. * set rndnum seed so can be replicated
. set seed 20190318
. gen errsim=rnormal(0,sf)

. replace pviewmont=pviewmont+errsim
(1,504 real changes made)

. regress pviewmont monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =     1,504
-------------+----------------------------------   F(3, 1500)      =      3.35
       Model |  6.2583e+10         3  2.0861e+10   Prob > F        =    0.0185
    Residual |  9.3476e+12     1,500  6.2317e+09   R-squared       =    0.0067
-------------+----------------------------------   Adj R-squared   =    0.0047
       Total |  9.4102e+12     1,503  6.2609e+09   Root MSE        =     78941

------------------------------------------------------------------------------
   pviewmont |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   568.2692   570.0658     1.00   0.319    -549.9417     1686.48
intervention |  -11618.79   8230.636    -1.41   0.158    -27763.56    4525.991
   postslope |  -1155.076    893.594    -1.29   0.196    -2907.903      597.75
       _cons |   51521.53   5841.437     8.82   0.000     40063.28    62979.78
------------------------------------------------------------------------------

. * now aggregate, and see that regression standard errors and pvalues are about the
same
. * coeffcients are exactly the same except for rounding because they do not depend on
simulation
. * the Root mean square error is about rmse of disagg model * sqrt(47), or about 7
times as high as mean
. collapse (mean) pviewmont , by( monthindex intervention postslope)

. regress pviewmont monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =        32
-------------+----------------------------------   F(3, 28)        =      3.18
       Model |  1.3316e+09         3   443853226   Prob > F        =    0.0392
    Residual |  3.9062e+09        28   139508526   R-squared       =    0.2542
-------------+----------------------------------   Adj R-squared   =    0.1743
       Total |  5.2378e+09        31   168961239   Root MSE        =     11811

------------------------------------------------------------------------------
   pviewmont |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   568.2691   584.7501     0.97   0.339    -629.5372    1766.075
intervention |  -11618.78   8442.648    -1.38   0.180    -28912.77    5675.196
   postslope |  -1155.076   916.6119    -1.26   0.218    -3032.671    722.5181
       _cons |   51521.53   5991.905     8.60   0.000     39247.67    63795.39
------------------------------------------------------------------------------


.
. *
. * END Simulation
. *
.
.
. use orig48long32, clear

. drop if artnames=="Hamas"
(0 observations deleted)

. *
. * large changes in standard errors and stat. sign. with removal of a single
observation is another sign of a poor model
```

```
. *
. preserve

. keep if highprivind==1
(512 observations deleted)

. collapse (median) pageviews, by( monthindex intervention postslope highpriv)

. regress pageviews monthindex intervention postslope if highpriv==1

      Source |       SS           df       MS      Number of obs   =        32
-------------+----------------------------------   F(3, 28)        =      2.98
       Model |  13595332.7         3  4531777.56   Prob > F        =    0.0482
    Residual |  42544868.8        28   1519459.6   R-squared       =    0.2422
-------------+----------------------------------   Adj R-squared   =    0.1610
       Total |  56140201.5        31  1810974.24   Root MSE        =    1232.7

------------------------------------------------------------------------------
   pageviews |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   123.6005   61.02594     2.03   0.052    -1.405487    248.6065
intervention |  -1336.267   881.0953    -1.52   0.141    -3141.109    468.5747
   postslope |  -189.8362   95.65985    -1.98   0.057    -385.7865    6.114118
       _cons |   6285.478   625.3298    10.05   0.000     5004.548    7566.408
------------------------------------------------------------------------------

. restore

. preserve

. * possible error since recruitment and fundamentalism have exact same page views
nearly every month
. * thus show results without as well as with
. drop if artnames=="Recruitment" | artnames=="Fundamentalism"
(64 observations deleted)

. keep if highprivind==1
(480 observations deleted)

. collapse (median) pageviews, by( monthindex intervention postslope highpriv)

. regress pageviews monthindex intervention postslope if highpriv==1

      Source |       SS           df       MS      Number of obs   =        32
-------------+----------------------------------   F(3, 28)        =      4.55
       Model |  9185572.85         3  3061857.62   Prob > F        =    0.0102
    Residual |  18850621.1        28   673236.47   R-squared       =    0.3276
-------------+----------------------------------   Adj R-squared   =    0.2556
       Total |    28036194        31  904393.355   Root MSE        =    820.51

------------------------------------------------------------------------------
   pageviews |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   93.56127   40.62129     2.30   0.029     10.35233    176.7702
intervention |  -1379.924    586.492    -2.35   0.026    -2581.298   -178.5493
   postslope |  -117.9791     63.675    -1.85   0.074    -248.4115    12.45319
       _cons |   6070.125   416.2444    14.58   0.000     5217.487    6922.763
------------------------------------------------------------------------------

. restore

. preserve
. collapse (median) pageviews, by( monthindex intervention postslope)

. regress pageviews monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =        32
-------------+----------------------------------   F(3, 28)        =      8.18
       Model |  84545042.9         3    28181681   Prob > F        =    0.0005
    Residual |    96510363        28  3446798.68   R-squared       =    0.4670
-------------+----------------------------------   Adj R-squared   =    0.4098
       Total |   181055406        31  5840496.96   Root MSE        =    1856.6

------------------------------------------------------------------------------
   pageviews |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   374.8799    91.9132     4.08   0.000     186.6043    563.1556
intervention |  -3299.076   1327.047    -2.49   0.019    -6017.408   -580.7433
   postslope |  -535.3763   144.0765    -3.72   0.001    -830.5036    -240.249
       _cons |   9601.022     941.83    10.19   0.000     7671.771    11530.27
------------------------------------------------------------------------------

. restore

. * now without possibly error data
. drop if artnames=="Fundamentalism" | artnames=="Recruitment"
(64 observations deleted)

. collapse (median) pageviews, by( monthindex intervention postslope)

. regress pageviews monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =        32
-------------+----------------------------------   F(3, 28)        =     17.36
       Model |  72354244.3         3  24118081.4   Prob > F        =    0.0000
    Residual |  38905201.2        28  1389471.47   R-squared       =    0.6503
-------------+----------------------------------   Adj R-squared   =    0.6129
       Total |   111259446        31  3589014.37   Root MSE        =    1178.8

------------------------------------------------------------------------------
   pageviews |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   315.9363   58.35724     5.41   0.000     196.3969    435.4757
intervention |  -4298.331   842.5644    -5.10   0.000    -6024.246   -2572.416
   postslope |  -342.8184   91.47658    -3.75   0.001    -530.1997   -155.4371
       _cons |   8841.338   597.9838    14.79   0.000     7616.424    10066.25
------------------------------------------------------------------------------

. *
. * demonstrate that errors are correlated with articles, meaning disggregation or
some type of adjustment is needed
. * Also shows that stat significance does not exist for overall data
. use orig48long32, clear

. regress pageviews monthindex intervention postslope if artnames!="Fundamentalism" &
artnames!="Recruitment"

      Source |       SS           df       MS      Number of obs   =     1,440
-------------+----------------------------------   F(3, 1436)      =      3.37
       Model |  6.7546e+10         3  2.2515e+10   Prob > F        =    0.0178
    Residual |  9.5866e+12     1,436  6.6759e+09   R-squared       =    0.0070
-------------+----------------------------------   Adj R-squared   =    0.0049
       Total |  9.6541e+12     1,439  6.7089e+09   Root MSE        =     81706

------------------------------------------------------------------------------
```

```
   pageviews |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   752.6646   603.0018     1.25   0.212    -430.1942    1935.523
intervention |  -14970.22   8706.167    -1.72   0.086    -32048.39    2107.947
   postslope |  -1179.932   945.2219    -1.25   0.212    -3034.096    674.2313
       _cons |   49658.62    6178.93     8.04   0.000     37537.93    61779.32
------------------------------------------------------------------------------

. regress pageviews monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =     1,504
-------------+----------------------------------   F(3, 1500)      =      3.86
       Model |  7.4228e+10         3  2.4743e+10   Prob > F        =    0.0091
    Residual |  9.6056e+12     1,500  6.4037e+09   R-squared       =    0.0077
-------------+----------------------------------   Adj R-squared   =    0.0057
       Total |  9.6798e+12     1,503  6.4403e+09   Root MSE        =     80023

------------------------------------------------------------------------------
   pageviews |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   881.2874   577.8797     1.53   0.127    -252.2505    2014.825
intervention |  -14757.81   8343.452    -1.77   0.077    -31123.88    1608.265
   postslope |  -1436.449   905.8423    -1.59   0.113    -3213.301    340.4031
       _cons |   48705.37   5921.504     8.23   0.000     37090.07    60320.68
------------------------------------------------------------------------------

. predict residual1, residual

. * stat sign correlation between articles and residuals mean model is insufficient
(see p-value and f-statistic)
. anova residual1 artnum

                         Number of obs =      1,504    R-squared     =  0.9258
                         Root MSE      =    22124.8    Adj R-squared =  0.9234

                  Source | Partial SS         df         MS        F    Prob>F
              -----------+----------------------------------------------------
                   Model |  8.892e+12         46   1.933e+11    394.91  0.0000
                         |
                  artnum |  8.892e+12         46   1.933e+11    394.91  0.0000
                         |
                Residual |  7.132e+11      1,457   4.895e+08  
              -----------+----------------------------------------------------
                   Total |  9.606e+12      1,503   6.391e+09  

. * note same coefficients in agg results
. collapse (mean) pageviews, by( monthindex intervention postslope)

. regress pageviews monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =        32
-------------+----------------------------------   F(3, 28)        =     24.85
       Model |  1.5793e+09         3   526437311   Prob > F        =    0.0000
    Residual |   593272771        28  21188313.2   R-squared       =    0.7269
-------------+----------------------------------   Adj R-squared   =    0.6977
       Total |  2.1726e+09        31  70083377.5   Root MSE        =    4603.1

------------------------------------------------------------------------------
   pageviews |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   881.2874   227.8862     3.87   0.001     414.4836    1348.091
intervention |  -14757.81   3290.232    -4.49   0.000    -21497.54   -8018.073
   postslope |  -1436.449    357.218    -4.02   0.000    -2168.177    -704.721
```

```
       _cons |   48705.37   2335.139    20.86   0.000     43922.06    53488.69
------------------------------------------------------------------------------


.
. *
. * show art is also stat sign for 31 high privacy
. use orig48long32, clear

. keep if highpriv==1
(512 observations deleted)

. regress pageviews monthindex intervention postslope if artnames!="Fundamentalism" &
artnames!="Recruitment"

      Source |       SS           df       MS      Number of obs   =       960
-------------+----------------------------------   F(3, 956)       =      4.20
       Model |  1.3198e+10         3  4.3994e+09   Prob > F        =    0.0058
    Residual |  1.0017e+12       956  1.0478e+09   R-squared       =    0.0130
-------------+----------------------------------   Adj R-squared   =    0.0099
       Total |  1.0149e+12       959  1.0582e+09   Root MSE        =     32369

------------------------------------------------------------------------------
   pageviews |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   823.6276   292.5762     2.82   0.005     249.4618    1397.793
intervention |  -8112.912   4224.229    -1.92   0.055    -16402.74    176.9203
   postslope |  -1145.897   458.6213    -2.50   0.013    -2045.918   -245.8766
       _cons |    14796.3   2998.014     4.94   0.000     8912.854    20679.75
------------------------------------------------------------------------------

. regress pageviews monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =       992
-------------+----------------------------------   F(3, 988)       =      5.18
       Model |  1.6582e+10         3  5.5273e+09   Prob > F        =    0.0015
    Residual |  1.0532e+12       988  1.0660e+09   R-squared       =    0.0155
-------------+----------------------------------   Adj R-squared   =    0.0125
       Total |  1.0698e+12       991  1.0795e+09   Root MSE        =     32650

------------------------------------------------------------------------------
   pageviews |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   918.8429   290.3169     3.16   0.002     349.1343    1488.552
intervention |  -8179.243   4191.609    -1.95   0.051    -16404.72    46.23536
   postslope |  -1340.458   455.0798    -2.95   0.003    -2233.492   -447.4243
       _cons |   15198.27   2974.863     5.11   0.000     9360.491    21036.04
------------------------------------------------------------------------------

. predict residual1, residual

. * stat sign correlation between articles and residuals mean model is insufficient
(see p-value and f-statistic)
. anova residual1 artnum

                         Number of obs =        992    R-squared     =  0.8558
                         Root MSE      =    12570.6    Adj R-squared =  0.8513

                  Source | Partial SS         df         MS        F    Prob>F
              -----------+----------------------------------------------------
                   Model |  9.014e+11         30   3.005e+10    190.14  0.0000
                         |
                  artnum |  9.014e+11         30   3.005e+10    190.14  0.0000
                         |
                Residual |  1.519e+11        961   1.580e+08
              -----------+----------------------------------------------------
                   Total |  1.053e+12        991   1.063e+09

. * note same coefficients in agg results
. collapse (mean) pageviews, by( monthindex intervention postslope)

. regress pageviews monthindex intervention postslope

      Source |       SS           df       MS      Number of obs   =        32
-------------+----------------------------------   F(3, 28)        =     20.87
       Model |   534899840         3   178299947   Prob > F        =    0.0000
    Residual |   239215204        28  8543400.16   R-squared       =    0.6910
-------------+----------------------------------   Adj R-squared   =    0.6579
       Total |   774115045        31  24971453.1   Root MSE        =    2922.9

------------------------------------------------------------------------------
   pageviews |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  monthindex |   918.8429   144.7056     6.35   0.000     622.4269    1215.259
intervention |  -8179.243   2089.266    -3.91   0.001    -12458.91   -3899.577
   postslope |  -1340.458     226.83    -5.91   0.000    -1805.099   -875.8181
       _cons |   15198.27   1482.791    10.25   0.000     12160.91    18235.63
------------------------------------------------------------------------------

.
. log close
      name:  <unnamed>
       log:
D:\clients_2018\DOJ_Wiki_NSA\programsdata\penneyreply\regression_effects_20190318.log
  log type:  text
 closed on:  19 Mar 2019, 11:01:40
```